Part II

Foundations
3 Goals

- Gain knowledge about efficient algorithms for important problems, i.e., learn how to solve certain types of problems efficiently.
- Learn how to analyze and judge the efficiency of algorithms.
- Learn how to design efficient algorithms.
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4 Modelling Issues

What do you measure?

▶ Memory requirement

▶ Running time

▶ Number of comparisons

▶ Number of multiplications

▶ Number of hard-disc accesses

▶ Program size

▶ Power consumption

▶ …
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How do you measure?

- Implementing and testing on representative inputs
  - How do you choose your inputs?
  - May be very time-consuming.
  - Very reliable results if done correctly.
  - Results only hold for a specific machine and for a specific set of inputs.

- Theoretical analysis in a specific model of computation.
  - Gives asymptotic bounds like \( O(n^2) \).
  - Typically focuses on the worst case.
  - Can give lower bounds like \( \Omega(n \log n) \) comparisons in the worst case.
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**Input length**
The theoretical bounds are usually given by a function $f : \mathbb{N} \rightarrow \mathbb{N}$ that maps the input length to the running time (or storage space, comparisons, multiplications, program size etc.).

The input length may e.g. be:
- the size of the input (number of bits)
- the number of arguments

**Example 1**
Suppose $n$ numbers from the interval $\{1, \ldots, N\}$ have to be sorted. In this case we usually say that the input length is $n$, instead of e.g. $n \log N$, which would be the number of bits required to encode the input.
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How to measure performance

1. Calculate running time and storage space etc. on a simplified, idealized model of computation, e.g. Random Access Machine (RAM), Turing Machine (TM).

2. Calculate number of certain basic operations: comparisons, multiplications, harddisc accesses.

Version 2 is often easier, but focusing on one type of operation makes it more difficult to obtain meaningful results.
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Turing Machine

- Very simple model of computation.
  - Only the “current” memory location can be altered.
  - Very good model for discussing computability, or polynomial vs. exponential time.
  - Some simple problems like recognizing whether input is of the form $xx$, where $x$ is a string, have quadratic lower bound.

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Random Access Machine (RAM)

- Input tape and output tape (sequences of zeros and ones; unbounded length).
- Memory unit: infinite but countable number of registers $R[0], R[1], R[2], \ldots$.
- Registers hold integers.
- Indirect addressing.

Note that in the picture on the right the tapes are one-directional, and that a READ- or WRITE-operation always advances its tape.
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Operations

- input operations (input tape $\rightarrow R[i]$)
  - READ $i$
- output operations ($R[i] \rightarrow$ output tape)
  - WRITE $i$
- register-register transfers
  - $R[j] := R[i]$
  - $R[i] := R[j]$
- indirect addressing
  - $R[j] := R[R[i]]$
  - $R[R[i]] := R[j]$
    loads the content of the $R[i]$-th register into the $j$-th register
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- branching (including loops) based on comparisons
  - jump $x$
    - jumps to position $x$ in the program;
    - sets instruction counter to $x$;
    - reads the next operation to perform from register $R[x]$.
  - jumpz $x \ R[i]$
    - jump to $x$ if $R[i] = 0$
    - if not the instruction counter is increased by 1;
  - jumpi $i$
    - jump to $R[i]$ (indirect jump);

- arithmetic instructions: $+, -, \times, /$
  - $R[i] := R[j] + R[k]$;
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The jump-directives are very close to the jump-instructions contained in the assembler language of real machines.
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Model of Computation

- **uniform** cost model
  Every operation takes time 1.

- **logarithmic** cost model
  The cost depends on the content of memory cells:
  - The time for a step is equal to the largest operand involved;
  - The storage space of a register is equal to the length (in bits) of the largest value ever stored in it.

Bounded word RAM model: cost is uniform but the largest value stored in a register may not exceed $2^w$, where usually $w = \log_2 n$.

The latter model is quite realistic as the word-size of a standard computer that handles a problem of size $n$ must be at least $\log_2 n$ as otherwise the computer could either not store the problem instance or not address all its memory.
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The latter model is quite realistic as the word-size of a standard computer that handles a problem of size $n$ must be at least $\log_2 n$ as otherwise the computer could either not store the problem instance or not address all its memory.
4 Modelling Issues

Example 2

Algorithm 1 RepeatedSquaring(n)

1: \( r \leftarrow 2; \)
2: \textbf{for} \( i = 1 \rightarrow n \) \textbf{do}
3: \( r \leftarrow r^2 \)
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\begin{align*}
\text{running time:} & \quad \text{uniform model:} & n \text{ steps} \\
& \quad \text{logarithmic model:} & 1 + 2 + 4 + \cdots + 2^n = 2^{n+1} - 1 = \Theta(2^n) \\
\text{space requirement:} & \quad \text{uniform model:} & O(1) \\
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There are different types of complexity bounds:

- **best-case complexity:**
  \[ C_{bc}(n) := \min \{ C(x) \mid |x| = n \} \]
  Usually easy to analyze, but not very meaningful.

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We are usually not interested in exact running times, but only in an asymptotic classification of the running time, that ignores constant factors and constant additive offsets.

We are usually interested in the running times for large values of $n$. Then constant additive terms do not play an important role.

An exact analysis (e.g., exactly counting the number of operations in a RAM) may be hard, but wouldn't lead to more precise results as the computational model is already quite a distance from reality.

A linear speed-up (i.e., by a constant factor) is always possible by e.g., implementing the algorithm on a faster machine.

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Formal Definition

Let $f$ denote functions from $\mathbb{N}$ to $\mathbb{R}^+$. 

$\mathcal{O}(f) = \{ g \mid \exists c > 0 \exists n_0 \in \mathbb{N}_0 \forall n \geq n_0 : [g(n) \leq c \cdot f(n)] \}$

(set of functions that asymptotically grow not faster than $f$)

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There is an equivalent definition using limes notation (assuming that the respective limes exists). $f$ and $g$ are functions from $\mathbb{N}_0$ to $\mathbb{R}_0^+$.

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Abuse of notation

1. People write $f = \mathcal{O}(g)$, when they mean $f \in \mathcal{O}(g)$. This is not an equality (how could a function be equal to a set of functions).

2. People write $f(n) = \mathcal{O}(g(n))$, when they mean $f \in \mathcal{O}(g)$, with $f : \mathbb{N} \to \mathbb{R}^+, n \mapsto f(n)$, and $g : \mathbb{N} \to \mathbb{R}^+, n \mapsto g(n)$.

3. People write e.g. $h(n) = f(n) + o(g(n))$ when they mean that there exists a function $z : \mathbb{N} \to \mathbb{R}^+, n \mapsto z(n), z \in o(g)$ such that $h(n) = f(n) + z(n)$.

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2. In this context $f(n)$ does not mean the function $f$ evaluated at $n$, but instead it is a shorthand for the function itself (leaving out domain and codomain and only giving the rule of correspondence of the function).

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How do we interpret an expression like:

\[ 2n^2 + 3n + 1 = 2n^2 + \Theta(n) \]

Here, \( \Theta(n) \) stands for an anonymous function in the set \( \Theta(n) \) that makes the expression true.

Note that \( \Theta(n) \) is on the right hand side, otw. this interpretation is wrong.
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How do we interpret an expression like:

\[ \sum_{i=1}^{n} \Theta(i) = \Theta(n^2) \]

Careful!

“It is understood” that every occurrence of an \( \Theta \)-symbol (or \( \Theta, \Omega, \omega \)) on the left represents one anonymous function.

Hence, the left side is not equal to

\[ \Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n) \]

\( \Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n) \) does not really have a reasonable interpretation.
Asymptotic Notation in Equations

How do we interpret an expression like:

$$\sum_{i=1}^{n} \Theta(i) = \Theta(n^2)$$

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\( \Theta(1) + \Theta(2) + \cdots + \Theta(n-1) + \Theta(n) \) does not really have a reasonable interpretation.
Asymptotic Notation in Equations

We can view an expression containing asymptotic notation as generating a set:

\[ n^2 \cdot \Theta(n) + \Theta(\log n) \]

represents

\[ \left\{ f : \mathbb{N} \to \mathbb{R}^+ \mid f(n) = n^2 \cdot g(n) + h(n) \right\} \]

with \( g(n) \in \Theta(n) \) and \( h(n) \in \Theta(\log n) \)

Recall that according to the previous slide e.g. the expressions \( \sum_{i=1}^{n} \Theta(i) \) and \( \sum_{i=1}^{n/2} \Theta(i) + \sum_{i=n/2+1}^{n} \Theta(i) \) generate different sets.
Asymptotic Notation in Equations

Then an asymptotic equation can be interpreted as containment btw. two sets:

\[ n^2 \cdot O(n) + O(\log n) = \Theta(n^2) \]

represents

\[ n^2 \cdot O(n) + O(\log n) \subseteq \Theta(n^2) \]

Note that the equation does not hold.
Lemma 3

Let \( f, g \) be functions with the property
\[
\exists n_0 > 0 \ \forall n \geq n_0 : f(n) > 0 \text{ (the same for } g). \]
Then
\[
\begin{align*}
&\text{\( c \cdot f(n) \in \Theta(f(n)) \) for any constant } c \\
&\text{\( \Theta(f(n)) + \Theta(g(n)) = \Theta(f(n) + g(n)) \) } \\
&\text{\( \Theta(f(n)) \cdot \Theta(g(n)) = \Theta(f(n) \cdot g(n)) \) } \\
&\text{\( \Theta(f(n)) + \Theta(g(n)) = \Theta(\max\{f(n), g(n)\}) \) }
\end{align*}
\]

The expressions also hold for \( \Omega \). Note that this means that
\[
f(n) + g(n) \in \Theta(\max\{f(n), g(n)\}).
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Lemma 3

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- \( c \cdot f(n) \in \Theta(f(n)) \) for any constant \( c \)
- \( \Theta(f(n)) + \Theta(g(n)) = \Theta(f(n) + g(n)) \)
- \( \Theta(f(n)) \cdot \Theta(g(n)) = \Theta(f(n) \cdot g(n)) \)
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- $c \cdot f(n) \in \Theta(f(n))$ for any constant $c$
- $\Theta(f(n)) + \Theta(g(n)) = \Theta(f(n) + g(n))$
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- $c \cdot f(n) \in \Theta(f(n))$ \textit{for any constant $c$}
- $\Theta(f(n)) + \Theta(g(n)) = \Theta(f(n) + g(n))$
- $\Theta(f(n)) \cdot \Theta(g(n)) = \Theta(f(n) \cdot g(n))$
- $\Theta(f(n)) + \Theta(g(n)) = \Theta(\max\{f(n), g(n)\})$

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$f(n) + g(n) \in \Theta(\max\{f(n), g(n)\})$. 
Asymptotic Notation

Comments

▶ Do not use asymptotic notation within induction proofs.
▶ For any constants $a, b$ we have $\log_a n = \Theta(\log_b n)$. Therefore, we will usually ignore the base of a logarithm within asymptotic notation.
▶ In general $\log n = \log_2 n$, i.e., we use 2 as the default base for the logarithm.
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Asymptotic Notation

In general asymptotic classification of running times is a good measure for comparing algorithms:

- If the running time analysis is tight and actually occurs in practise (i.e., the asymptotic bound is not a purely theoretical worst-case bound), then the algorithm that has better asymptotic running time will always outperform a weaker algorithm for large enough values of $n$.

- However, suppose that I have two algorithms:

  Algorithm A. Running time $f(n) = 1000 \log n = O(\log n)$.

  Algorithm B. Running time $g(n) = \log_2 n$.

  Clearly $f(n) = o(g(n))$. However, as long as $\log n \leq 1000$, Algorithm B will be more efficient.
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Clearly $f = o(g)$. However, as long as $\log n \leq 1000$ Algorithm B will be more efficient.
6 Recurrences

Algorithm 2 mergesort(list $L$)

1: $n \leftarrow \text{size}(L)$
2: if $n \leq 1$ return $L$
3: $L_1 \leftarrow L[1 \cdots \lfloor \frac{n}{2} \rfloor ]$
4: $L_2 \leftarrow L[\lceil \frac{n}{2} \rceil + 1 \cdots n ]$
5: mergesort($L_1$)
6: mergesort($L_2$)
7: $L \leftarrow \text{merge}(L_1, L_2)$
8: return $L$

This algorithm requires $T(n) = T(\lceil \frac{n}{2} \rceil ) + T(\lfloor \frac{n}{2} \rfloor ) + O(n)$ comparisons when $n > 1$ and 0 comparisons when $n \leq 1$. 

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This algorithm requires

$$T(n) = T\left(\lceil \frac{n}{2} \rceil \right) + T\left(\lfloor \frac{n}{2} \rfloor \right) + \Theta(n) \leq 2T\left(\lceil \frac{n}{2} \rceil \right) + \Theta(n)$$

comparisons when $n > 1$ and 0 comparisons when $n \leq 1$. 
How do we bring the expression for the number of comparisons (≈ running time) into a **closed form**?

For this we need to solve the recurrence.
Recurrences

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For this we need to **solve** the recurrence.
Methods for Solving Recurrences

1. **Guessing + Induction**
   Guess the right solution and prove that it is correct via induction. It needs experience to make the right guess.

2. **Master Theorem**
   For a lot of recurrences that appear in the analysis of algorithms this theorem can be used to obtain tight asymptotic bounds. It does not provide exact solutions.

3. **Characteristic Polynomial**
   Linear homogenous recurrences can be solved via this method.
4. Generating Functions
A more general technique that allows to solve certain types of linear inhomogenous relations and also sometimes non-linear recurrence relations.

5. Transformation of the Recurrence
Sometimes one can transform the given recurrence relations so that it e.g. becomes linear and can therefore be solved with one of the other techniques.
First we need to get rid of the $\mathcal{O}$-notation in our recurrence:

$$T(n) \le \begin{cases} 
2T([n/2]) + cn & n \ge 2 \\
0 & \text{otherwise}
\end{cases}$$

Informal way:
First we need to get rid of the $\Theta$-notation in our recurrence:

\[
T(n) \leq \begin{cases} 
2T(\lceil \frac{n}{2} \rceil) + cn & n \geq 2 \\
0 & \text{otherwise}
\end{cases}
\]

**Informal way:**
Assume that instead we have

\[
T(n) \leq \begin{cases} 
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Assume that instead we have

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One way of solving such a recurrence is to **guess** a solution, and check that it is correct by plugging it in.
Suppose we guess $T(n) \leq dn \log n$ for a constant $d$. 
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$$\leq 2\left(d \frac{n}{2} \log \frac{n}{2}\right) + cn$$

if we choose $d \geq c$. Formally, this is not correct if $n$ is not a power of 2. Also even in this case one would need to do an induction proof.
Suppose we guess $T(n) \leq dn \log n$ for a constant $d$. Then

$$T(n) \leq 2T\left(\frac{n}{2}\right) + cn$$

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$$= dn(\log n - 1) + cn$$
6.1 Guessing+Induction

Suppose we guess $T(n) \leq dn \log n$ for a constant $d$. Then

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$$\leq dn \log n$$

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Formally, this is not correct if \( n \) is not a power of 2. Also even in this case one would need to do an induction proof.
How do we get a result for all values of $n$?
6.1 Guessing+Induction

How do we get a result for all values of \( n \)?

We consider the following recurrence instead of the original one:

\[
T(n) \leq \begin{cases} 
2T\left(\left\lfloor \frac{n}{2} \right\rfloor \right) + cn & n \geq 16 \\
b & \text{otherwise}
\end{cases}
\]

Note that we can do this as for constant-sized inputs the running time is always some constant (\( b \) in the above case).
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We also make a guess of $T(n) \leq dn \log n$ and get

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T(n) \leq 2T\left(\left\lfloor \frac{n}{2} \right\rfloor \right) + cn
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\leq 2\left( d\left\lfloor \frac{n}{2} \right\rfloor \log \left\lfloor \frac{n}{2} \right\rfloor \right) + cn
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\[
\left\lfloor \frac{n}{2} \right\rfloor \leq \frac{n}{2} + 1
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\leq 2\left(d\left\lfloor \frac{n}{2} \right\rfloor \log \left\lfloor \frac{n}{2} \right\rfloor\right) + cn
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\[
\leq dn \log \left(\frac{9}{16}n\right) + 2d \log n + cn
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\[
\log \frac{9}{16}n = \log n + (\log 9 - 4)
\]
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\[
\leq 2\left(d\left\lceil \frac{n}{2} \right\rceil \log \left\lceil \frac{n}{2} \right\rceil\right) + cn
\]

\[
\leq 2(d(n/2 + 1) \log(n/2 + 1)) + cn
\]

\[
\leq dn \log \left(\frac{9}{16} n\right) + 2d \log n + cn
\]

\[
\log \frac{9}{16} n = \log n + (\log 9 - 4)
\]

\[
= dn \log n + (\log 9 - 4)dn + 2d \log n + cn
\]
We also make a guess of $T(n) \leq dn \log n$ and get

$$T(n) \leq 2T\left(\left\lceil \frac{n}{2} \right\rceil \right) + cn \leq 2\left( d\left\lceil \frac{n}{2} \right\rceil \log \left\lceil \frac{n}{2} \right\rceil \right) + cn \leq 2\left( d\left(\frac{n}{2} + 1\right) \log\left(\frac{n}{2} + 1\right) \right) + cn \leq dn \log \left(\frac{9}{16}n\right) + 2d \log n + cn \leq dn \log n + \left(\log 9 - 4\right)dn + 2d \log n + cn$$

$\left\lceil \frac{n}{2} \right\rceil \leq \frac{n}{2} + 1$

$\frac{n}{2} + 1 \leq \frac{9}{16}n$

$log \frac{9}{16}n = log n + (log 9 - 4)$

$log n \leq \frac{n}{4}$
6.1 Guessing+Induction

We also make a guess of $T(n) \leq dn \log n$ and get

$$T(n) \leq 2T\left(\left\lfloor \frac{n}{2} \right\rfloor \right) + cn$$

$$\leq 2 \left( d \left\lfloor \frac{n}{2} \right\rfloor \log \left\lfloor \frac{n}{2} \right\rfloor \right) + cn$$

$$\leq 2 \left( d \left( n/2 + 1 \right) \log (n/2 + 1) \right) + cn$$

$$\leq dn \log \left( \frac{9}{16} n \right) + 2d \log n + cn$$

$$= dn \log n + (\log 9 - 4)dn + 2d \log n + cn$$

$$\leq dn \log n + (\log 9 - 3.5)dn + cn$$
We also make a guess of $T(n) \leq dn \log n$ and get

\[
T(n) \leq 2T\left(\left\lfloor \frac{n}{2} \right\rfloor \right) + cn \\
\leq 2\left( d\left\lfloor \frac{n}{2} \right\rfloor \log \left\lfloor \frac{n}{2} \right\rfloor \right) + cn \\
\leq 2\left( d\left(\frac{n}{2} + 1\right) \log\left(\frac{n}{2} + 1\right) \right) + cn \\
\leq d n \log \left(\frac{9}{16} n\right) + 2d \log n + cn \\
= d n \log n + (\log 9 - 4)dn + 2d \log n + cn \\
\leq d n \log n + (\log 9 - 3.5)dn + cn \\
\leq d n \log n - 0.33dn + cn
\]
6.1 Guessing+Induction

We also make a guess of $T(n) \leq dn \log n$ and get

$$T(n) \leq 2T\left(\left\lfloor \frac{n}{2} \right\rfloor\right) + cn$$

$$\leq 2\left(d\left\lfloor \frac{n}{2} \right\rfloor \log \left\lfloor \frac{n}{2} \right\rfloor\right) + cn$$

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$$\leq dn \log n + \left(\log 9 - 3.5\right)dn + cn$$

$$\leq dn \log n - 0.33dn + cn$$

$$\leq dn \log n$$

for a suitable choice of $d$. 
6.2 Master Theorem

**Lemma 4**

Let \( a \geq 1, b \geq 1 \) and \( \epsilon > 0 \) denote constants. Consider the recurrence

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

**Case 1.**

If \( f(n) = O\left(n^{\log_b(a) - \epsilon}\right) \) then \( T(n) = \Theta(n^{\log_b a}) \).

**Case 2.**

If \( f(n) = \Theta\left(n^{\log_b(a) \log^k n}\right) \) then \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}), k \geq 0 \).

**Case 3.**

If \( f(n) = \Omega\left(n^{\log_b(a) + \epsilon}\right) \) and for sufficiently large \( n \)

\[
a f\left(\frac{n}{b}\right) \leq c f(n) \quad \text{for some constant } c < 1 \]

then \( T(n) = \Theta(f(n)) \).

Note that the cases do not cover all possibilities.
6.2 Master Theorem

We prove the Master Theorem for the case that $n$ is of the form $b^\ell$, and we assume that the non-recursive case occurs for problem size 1 and incurs cost 1.
The Recursion Tree

The running time of a recursive algorithm can be visualized by a recursion tree:
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\[ f(n) \]

\[ af\left(\frac{n}{b}\right) \]
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\[
\begin{align*}
f(n) &= a f\left(\frac{n}{b}\right) \\
a^2 f\left(\frac{n}{b^2}\right) &\leq \alpha \left(\frac{n}{b^2}\right) \\
&\vdots \\
a^{\log_b a} n &\leq n^{\log_b a}
\end{align*}
\]
This gives

\[ T(n) = n^{\log_b a} + \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right). \]
Case 1. Now suppose that $f(n) \leq cn^{\log_b a-\epsilon}$. 
Case 1. Now suppose that \( f(n) \leq cn^{\log_b a - \epsilon} \).

\[
T(n) - n^{\log_b a}
\]
Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f \left( \frac{n}{b^i} \right)$$
Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon}$$
Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f \left( \frac{n}{b^i} \right)$$

$$\leq c \sum_{i=0}^{\log_b n - 1} a^i \left( \frac{n}{b^i} \right)^{\log_b a - \epsilon}$$

$$b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}$$
Case 1. Now suppose that \( f(n) \leq cn^{\log_b a - \epsilon} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left( \frac{n}{b^i} \right)^{\log_b a - \epsilon} \\
= c n^{\log_b a - \epsilon} \sum_{i=0}^{\log_b n - 1} (b^\epsilon)^i
\]

\[
b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}
\]
Case 1. Now suppose that $f(n) \leq cn^{\log_b a-\epsilon}$.

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

\[
\leq c \sum_{i=0}^{\log_b n-1} a^i \left(\frac{n}{b^i}\right)^{\log_b a-\epsilon}
\]

\[
b^{-i(\log_b a-\epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}
\]

\[
\sum_{i=0}^{k} q^i = \frac{q^{k+1} - 1}{q - 1}
\]
Case 1. Now suppose that \( f(n) \leq cn^{\log_b a-\epsilon} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right) \\
\leq c \sum_{i=0}^{\log_b n-1} a^i \left(\frac{n}{b^i}\right)^{\log_b a-\epsilon}
\]

\[
b^{-i(\log_b a-\epsilon)} = b^{\epsilon i}(b^{\log_b a})^{-i} = b^{\epsilon i}a^{-i}
\]

\[
\sum_{i=0}^{k} q^i = \frac{q^{k+1}-1}{q-1}
\]

\[
= cn^{\log_b a-\epsilon} (b^{\epsilon \log_b n - 1}) / (b^\epsilon - 1)
\]
Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$

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$$b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}$$

$$\sum_{i=0}^{k} q^i = \frac{q^{k+1} - 1}{q - 1}$$

$$= c n^{\log_b a - \epsilon} \left(\frac{b^{\epsilon \log_b n} - 1}{b^{\epsilon} - 1}\right)$$

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Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f \left( \frac{n}{b^i} \right)$$

$$\leq c \sum_{i=0}^{\log_b n - 1} a^i \left( \frac{n}{b^i} \right)^{\log_b a - \epsilon}$$

$$b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}$$

$$\sum_{i=0}^{k} q^i = \frac{q^{k+1} - 1}{q - 1}$$

$$\sum_{i=0}^{k} q^i = \frac{a^{k+1} - 1}{a - 1}$$

$$= cn^{\log_b a - \epsilon} (b^{\epsilon \log_b n} - 1) / (b^{\epsilon} - 1)$$

$$= cn^{\log_b a - \epsilon} (n^{\epsilon} - 1) / (b^{\epsilon} - 1)$$

$$= \frac{c}{b^{\epsilon} - 1} n^{\log_b a} (n^{\epsilon} - 1) / (n^{\epsilon})$$
Case 1. Now suppose that \( f(n) \leq cn^{\log_b a - \epsilon} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)
\]
\[
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon}
\]
\[
b^{-i(\log_b a - \epsilon)} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i}
\]
\[
\sum_{i=0}^{k} q^i = \frac{q^{k+1} - 1}{q - 1}
\]
\[
= c n^{\log_b a - \epsilon} \left( b^{\epsilon \log_b n} - 1 \right) / (b^\epsilon - 1)
\]
\[
= c n^{\log_b a - \epsilon} (n^\epsilon - 1) / (b^\epsilon - 1)
\]
\[
= \frac{c}{b^\epsilon - 1} n^{\log_b a} (n^\epsilon - 1) / (n^\epsilon)
\]

Hence,

\[
T(n) \leq \left( \frac{c}{b^\epsilon - 1} + 1 \right) n^{\log_b (a)}
\]
Case 1. Now suppose that $f(n) \leq cn^{\log_b a - \epsilon}$.

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

\[ \leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a - \epsilon} \]

\[ \frac{b^{-i(\log_b a - \epsilon)}}{b^{-i}} = b^{\epsilon i} (b^{\log_b a})^{-i} = b^{\epsilon i} a^{-i} \]

\[ \sum_{i=0}^{k} q^i = \frac{q^{k+1} - 1}{q - 1} \]

\[ = c n^{\log_b a - \epsilon} \left( b^{\epsilon \log_b n} - 1 \right) / (b^{\epsilon} - 1) \]

\[ = c n^{\log_b a - \epsilon} (n^\epsilon - 1) / (b^{\epsilon} - 1) \]

\[ = \frac{c}{b^{\epsilon} - 1} n^{\log_b a} (n^\epsilon - 1) / (n^\epsilon) \]

Hence,

\[ T(n) \leq \left( \frac{c}{b^{\epsilon} - 1} + 1 \right) n^{\log_b a} \]

\[ \Rightarrow T(n) = \mathcal{O}(n^{\log_b a}). \]
Case 2. Now suppose that \( f(n) \leq cn^{\log_b a} \).
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\[ T(n) - n^{\log_b a} \]
Case 2. Now suppose that $f(n) \leq cn^{\log_b a}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)$$
Case 2. Now suppose that $f(n) \leq cn^{\log_b a}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right) \leq c \sum_{i=0}^{\log_b n-1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}$$

Hence,$$T(n) = O(n^{\log_b a})$$
Case 2. Now suppose that $f(n) \leq cn^{\log_b a}$.

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

\[
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}
\]

\[
= cn^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1
\]
Case 2. Now suppose that $f(n) \leq cn^{\log_b a}$.

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T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)
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\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}
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= cn^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1
\]

\[
= cn^{\log_b a} \log_b n
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Case 2. Now suppose that $f(n) \leq cn^{\log_b a}$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}$$

$$= cn^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1$$

$$= cn^{\log_b a} \log_b n$$

Hence,

$$T(n) = O(n^{\log_b a} \log_b n)$$
Case 2. Now suppose that \( f(n) \leq cn^{\log_b a} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}
= cn^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1
= cn^{\log_b a} \log_b n
\]

Hence,

\[
T(n) = \mathcal{O}(n^{\log_b a} \log_b n) \quad \Rightarrow \quad T(n) = \mathcal{O}(n^{\log_b a} \log n).
\]
Case 2. Now suppose that $f(n) \geq cn^{\log_b a}$. 
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\[
T(n) - n^{\log_b a}
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$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$
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\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\
\geq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}
\]
Case 2. Now suppose that \( f(n) \geq cn^{\log_b a} \).

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T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right) \\
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$$\geq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a}$$

$$= cn^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1$$

$$= cn^{\log_b a} \log_b n$$
Case 2. Now suppose that \( f(n) \geq cn^{\log_b a} \).

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f \left( \frac{n}{b^i} \right) \\
\geq c \sum_{i=0}^{\log_b n - 1} a^i \left( \frac{n}{b^i} \right)^{\log_b a} \\
= cn^{\log_b a} \sum_{i=0}^{\log_b n - 1} 1 \\
= cn^{\log_b a} \log_b n
\]

Hence,

\[
T(n) = \Omega(n^{\log_b a} \log_b n)
\]
Case 2. Now suppose that $f(n) \geq cn^{\log_b a}$.

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right) \\
\geq c \sum_{i=0}^{\log_b n-1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \\
= cn^{\log_b a} \sum_{i=0}^{\log_b n-1} 1 \\
= cn^{\log_b a} \log_b n
\]

Hence,

\[
T(n) = \Omega(n^{\log_b a} \log_b n) \quad \Rightarrow \quad T(n) = \Omega(n^{\log_b a} \log n).
\]
Case 2. Now suppose that $f(n) \leq cn^{\log_b a}(\log_b(n))^k$. 

6.2 Master Theorem

Ernst Mayr, Harald Räcke
Case 2. Now suppose that $f(n) \leq cn^{\log_b a} (\log_b (n))^k$.

$$T(n) - n^{\log_b a}$$
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$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$
**Case 2.** Now suppose that $f(n) \leq cn^{\log_b a} (\log_b (n))^k$.

\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right) \\
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b \left(\frac{n}{b^i}\right)\right)^k
\]
Case 2. Now suppose that \( f(n) \leq cn^{\log_b a} (\log_b(n))^k \).

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

\[
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b \left(\frac{n}{b^i}\right)\right)^k
\]

\[n = b^\ell \Rightarrow \ell = \log_b n\]
Case 2. Now suppose that $f(n) \leq cn^{\log_b a} (\log_b (n))^k$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq c \sum_{i=0}^{\log_b n-1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b \left(\frac{n}{b^i}\right)\right)^k$$

$n = b^\ell \Rightarrow \ell = \log_b n$

$$= cn^{\log_b a} \sum_{i=0}^{\ell-1} \left(\log_b \left(\frac{b^\ell}{b^i}\right)\right)^k$$

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$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq c \sum_{i=0}^{\log_b n-1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b \left(\frac{n}{b^i}\right)\right)^k$$

\[n = b^\ell \Rightarrow \ell = \log_b n\]

$$= cn^{\log_b a} \sum_{i=0}^{\ell-1} \left(\log_b \left(\frac{b^\ell}{b^i}\right)\right)^k$$

$$= cn^{\log_b a} \sum_{i=0}^{\ell-1} (\ell - i)^k$$
Case 2. Now suppose that \( f(n) \leq cn^{\log_b a} (\log_b(n))^k \).

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

\[
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b \left(\frac{n}{b^i}\right)\right)^k
\]

\[
n = b^\ell \Rightarrow \ell = \log_b n
\]

\[
= cn^{\log_b a} \sum_{i=0}^{\ell-1} \left(\log_b \left(\frac{b^\ell}{b^i}\right)\right)^k
\]

\[
= cn^{\log_b a} \sum_{i=0}^{\ell-1} (\ell - i)^k
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6.2 Master Theorem
Case 2. Now suppose that \( f(n) \leq c n^{\log_b a} (\log_b(n))^k \).

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\]

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\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b\left(\frac{n}{b^i}\right)\right)^k
\]

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n = b^\ell \Rightarrow \ell = \log_b n
\]

\[
= cn^{\log_b a} \sum_{i=0}^{\ell - 1} \left(\log_b\left(\frac{b^\ell}{b^i}\right)\right)^k
\]

\[
= cn^{\log_b a} \sum_{i=0}^{\ell - 1} (\ell - i)^k
\]

\[
= cn^{\log_b a} \sum_{i=1}^{\ell} i^k \approx \frac{1}{k} \ell^{k+1}
\]
Case 2. Now suppose that \( f(n) \leq cn^{\log_b a} (\log_b(n))^k \).

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

\[
\leq c \sum_{i=0}^{\log_b n - 1} a^i \left( \frac{n}{b^i} \right)^{\log_b a} \cdot \left( \log_b \left( \frac{n}{b^i} \right) \right)^k
\]

\[
n = b^\ell \Rightarrow \ell = \log_b n
\]

\[
= c n^{\log_b a} \sum_{i=0}^{\ell - 1} \left( \log_b \left( \frac{b^\ell}{b^i} \right) \right)^k
\]

\[
= c n^{\log_b a} \sum_{i=0}^{\ell - 1} (\ell - i)^k
\]

\[
= c n^{\log_b a} \sum_{i=1}^\ell i^k
\]

\[
\approx \frac{c}{k} n^{\log_b a} \ell^{k+1}
\]
Case 2. Now suppose that $f(n) \leq cn^{\log_b a} (\log_b (n))^k$.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n - 1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq c \sum_{i=0}^{\log_b n - 1} a^i \left(\frac{n}{b^i}\right)^{\log_b a} \cdot \left(\log_b \left(\frac{n}{b^i}\right)\right)^k$$

$n = b^\ell \Rightarrow \ell = \log_b n$

$$= cn^{\log_b a} \sum_{i=0}^{\ell - 1} \left(\log_b \left(\frac{b^\ell}{b^i}\right)\right)^k$$

$$= cn^{\log_b a} \sum_{i=0}^{\ell - 1} (\ell - i)^k$$

$$= cn^{\log_b a} \sum_{i=1}^{\ell} i^k$$

$$\approx \frac{c}{k} n^{\log_b a} \ell^{k+1}$$

$\Rightarrow T(n) = \mathcal{O}(n^{\log_b a} \log^{k+1} n)$. 

6.2 Master Theorem
Case 3. Now suppose that \( f(n) \geq dn^{\log_b a + \epsilon} \), and that for sufficiently large \( n \): \( af(n/b) \leq cf(n) \), for \( c < 1 \).

Where did we use \( f(n) \geq \Omega(n^{\log_b a + \epsilon}) \)?
Case 3. Now suppose that $f(n) \geq dn^{\log_b a+\epsilon}$, and that for sufficiently large $n$: $af(n/b) \leq cf(n)$, for $c < 1$.

From this we get $a^i f(n/b^i) \leq c^i f(n)$, where we assume that $n/b^i-1 \geq n_0$ is still sufficiently large.
Case 3. Now suppose that \( f(n) \geq dn^{\log_b a + \epsilon} \), and that for sufficiently large \( n \): \( af(n/b) \leq cf(n) \), for \( c < 1 \).

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

Where did we use \( f(n) \geq \Omega(n^{\log_b a + \epsilon}) \)?
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\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)
\]

\[
\leq \sum_{i=0}^{\log_b n-1} c^i f(n) + O(n^{\log_b a})
\]

Where did we use \( f(n) \geq \Omega(n^{\log_b a + \epsilon}) \)?
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\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)
\]

\[
\leq \sum_{i=0}^{\log_b n-1} c^i f(n) + O(n^{\log_b a})
\]

\( q < 1 : \sum_{i=0}^{n} q^i = \frac{1-q^{n+1}}{1-q} \leq \frac{1}{1-q} \)

Where did we use \( f(n) \geq \Omega(n^{\log_b a+\epsilon}) \)?
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\[
T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)
\]

\[
\leq \sum_{i=0}^{\log_b n-1} c^i f(n) + O(n^{\log_b a})
\]

\[
q < 1 : \sum_{i=0}^{n} q^i = \frac{1-q^{n+1}}{1-q} \leq \frac{1}{1-q}
\]

\[
\leq \frac{1}{1-c} f(n) + O(n^{\log_b a})
\]

Where did we use \( f(n) \geq \Omega(n^{\log_b a + \epsilon}) \)?
Case 3. Now suppose that $f(n) \geq dn^{\log_b a + \epsilon}$, and that for sufficiently large $n$: $af(n/b) \leq cf(n)$, for $c < 1$.

From this we get $a^i f(n/b^i) \leq c^i f(n)$, where we assume that $n/b^{i-1} \geq n_0$ is still sufficiently large.

$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq \sum_{i=0}^{\log_b n-1} c^i f(n) + O(n^{\log_b a})$$

$q < 1 : \sum_{i=0}^{n} q^i = \frac{1-q^{n+1}}{1-q} \leq \frac{1}{1-q}$

$$\leq \frac{1}{1-c} f(n) + O(n^{\log_b a})$$

Hence,

$$T(n) \leq O(f(n))$$

Where did we use $f(n) \geq \Omega(n^{\log_b a + \epsilon})$?
Case 3. Now suppose that $f(n) \geq dn^{\log_b a + \epsilon}$, and that for sufficiently large $n$: $af(n/b) \leq cf(n)$, for $c < 1$.

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$$T(n) - n^{\log_b a} = \sum_{i=0}^{\log_b n-1} a^i f\left(\frac{n}{b^i}\right)$$

$$\leq \sum_{i=0}^{\log_b n-1} c^i f(n) + O(n^{\log_b a})$$

$q < 1: \sum_{i=0}^{n} q^i = \frac{1-q^{n+1}}{1-q} \leq \frac{1}{1-q}$

$$\leq \frac{1}{1 - c} f(n) + O(n^{\log_b a})$$

Hence,

$$T(n) \leq O(f(n)) \Rightarrow T(n) = \Theta(f(n)).$$

Where did we use $f(n) \geq \Omega(n^{\log_b a + \epsilon})$?
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{align*}
\text{A} & : 101011011 \\
\text{B} & : 100010101 \\
\text{Sum} & : 1011011101
\end{align*}
\]
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0
\end{array}
\quad\begin{array}{cccccccc}
A
\end{array}
\]

\[
\begin{array}{cccccccc}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1
\end{array}
\quad\begin{array}{cccccccc}
B
\end{array}
\]

\[
\begin{array}{cccccccc}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1
\end{array}
\]

This gives that two \( n \)-bit integers can be added in time \( O(n) \).
Example: Multiplying Two Integers

Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
\hline
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0
\end{array}
\]

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Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{c}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 0
\end{array}
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\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
\end{array}
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For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
\end{array}
\begin{array}{c}
1 \\
1 \\
\end{array}
\begin{array}{c}
A \\
B \\
\end{array}
\]

This gives that two $n$-bit integers can be added in time $O(n)$. 

6.2 Master Theorem 11. Apr. 2018

Ernst Mayr, Harald Räcke
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
\end{array}
\begin{array}{cccccccc}
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\
\end{array}
\hline
0 & 0
\end{array}
\]
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
0 & 0 & 0 & & & & &
\end{array}
\]

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For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccc}
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 \\
\hline
1 & 0 & 0 & 0 & 1 & 0 \\
1 & 1 & 1 & 1 \\
\hline
0 & 0 & 0 & 0 \\
\end{array}
\]

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\[
\begin{array}{cccc}
1 & 1 & 0 & 1 \\
1 & 0 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 \\
\end{array}
\begin{array}{cccc}
1 & 1 & 0 & 1 \\
0 & 1 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 \\
\end{array}
\]

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Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccc}
1 & 1 & 0 & 1 &  \boxed{1} & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & \boxed{1} & 0 & 0 & 1 & 1 \\
\hline
1 & 0 & 0 & 0 & 0 & 1
\end{array}
\]

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\[
\begin{array}{ccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 1 & 1 \\
\hline
0 & 1 & 0 & 0 & 0 & 1 & 1 \\
\end{array}
\]
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For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccc}
1 & 1 & 0 & 1 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 1 \\
\hline
0 & 1 & 0 & 0 & 0 & 0 \\
\end{array}
\]

This gives that two $n$-bit integers can be added in time $O(n)$. 

6.2 Master Theorem
Example: Multiplying Two Integers

Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 \\
\hline
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0
\end{array}
\]

This gives that two $n$-bit integers can be added in time $\mathcal{O}(n)$. 
Example: Multiplying Two Integers

Suppose we want to multiply two \( n \)-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{array}{c}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
\hline
1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 & 1 \\
\hline
0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
\end{array}
\]

This gives that two \( n \)-bit integers can be added in time \( O(n) \).
Example: Multiplying Two Integers

Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{c}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1
\end{array}
\]

\[
\begin{array}{c}
1 & 0 & 0 & 1 & 0 & 0 & 0 & 0
\end{array}
\]
Example: Multiplying Two Integers

Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccccccc}
1 & 1 & 0 & 0 & 1 & 1 & 0 & 1 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\
\hline
1 & 0 & 0 & 1 & 0 & 0 & 0 & 0
\end{array}
\]

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For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{cccccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & A \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & B \\
\hline
0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 &
\end{array}
\]

This gives that two $n$-bit integers can be added in time $O(n)$. 

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\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
\hline
0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\
\hline
1 & 1 & 0 & 0 & 1 & 0 & 0 & 0
\end{array}
\]
Example: Multiplying Two Integers

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For this we first need to be able to add two integers $A$ and $B$:

```
1 1 0 1 1 0 1 0 1
1 0 0 0 1 0 0 1 1
0 1 1 0 0 1 0 0 0
```

This gives that two $n$-bit integers can be added in time $O(n)$. 

6.2 Master Theorem
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Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$: 

\[
\begin{array}{cccccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 & 1 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 & 1 & 1 \\
0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 & 0
\end{array}
\]

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For this we first need to be able to add two integers \( A \) and \( B \):

\[
\begin{array}{cccccccc}
1 & 1 & 0 & 1 & 1 & 0 & 1 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 1 \\
1 & 0 & 1 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
\end{array}
\]

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Suppose we want to multiply two $n$-bit Integers, but our registers can only perform operations on integers of constant size.

For this we first need to be able to add two integers $A$ and $B$:

\[
\begin{array}{c}
1 1 0 1 1 0 1 0 1 \\
1 0 0 1 1 0 0 1 1 \\
\hline
1 0 1 1 0 0 1 0 0 0
\end{array}
\]

This gives that two $n$-bit integers can be added in time $O(n)$. 

6.2 Master Theorem

Ernst Mayr, Harald Räcke
Example: Multiplying Two Integers

Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

- This is also known as the "school method" for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.
Example: Multiplying Two Integers

Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccccc}
1 & 0 & 0 & 0 & 1 \\
\times & & & & & 1 & 0 & 1 & 1
\end{array}
\]

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.
Example: Multiplying Two Integers

Suppose that we want to multiply an \( n \)-bit integer \( A \) and an \( m \)-bit integer \( B \) \((m \leq n)\).

\[
\begin{array}{c}
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 \\
\end{array}
\]

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Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
1\ 0\ 0\ 0\ 1 \times 1\ 0\ 1\ 0\ 1
\]

\[
1\ 0\ 0\ 0\ 1
\]

• This is also known as the “school method” for multiplying integers.
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Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 & 1 \\
\times & 1 & 0 & 1 & 1 \\
\hline
& & 1 & 0 & 0 & 0 & 1
\end{array}
\]

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Suppose that we want to multiply an \( n \)-bit integer \( A \) and an \( m \)-bit integer \( B \) \((m \leq n)\).

\[
\begin{array}{cccccc}
1 & 0 & 0 & 0 & 1 & \times
\end{array}
\begin{array}{c}
1 & 0 & 1 & 1
\end{array}
\]

\[
\begin{array}{cccccc}
1 & 0 & 0 & 0 & 1 & \\
1 & 0 & 0 & 0 & 1 & 0
\end{array}
\]

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\[
\begin{array}{c}
1 & 0 & 0 & 0 & 1 \\
\times & & & & 1 & 0 & 1 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0
\end{array}
\]

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\[
\begin{array}{c}
1 \\
0 \\
0 \\
0 \\
1 \\
\times \\
1 \\
0 \\
0 \\
1 \\
1 \\
\end{array}
\]

\[
\begin{array}{c}
1 \\
0 \\
0 \\
0 \\
1 \\
1 \\
1 \\
0 \\
0 \\
0 \\
1 \\
0 \\
\end{array}
\]

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Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 & 1 \\
\times & 1 & 0 & 1 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & & & \\
\end{array}
\]

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Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccccc}
1 & 0 & 0 & 0 & 1 & \times \ 1 & 0 & 1 & 1 \\
& & & & \hline
1 & 0 & 0 & 0 & 1 &
\end{array}
\]

• This is also known as the “school method” for multiplying integers.

• Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.
Example: Multiplying Two Integers

Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
1 0 0 0 1 \times 1 0 1 1
\]

\[
\begin{array}{c}
1 0 0 0 1 \\
1 0 0 0 1 \\
0 0 0 1 0 \\
0 0 0 0 0 0 0 0
\end{array}
\]

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.
Example: Multiplying Two Integers

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\[
\begin{array}{cccc}
1 & 0 & 0 & 0 & 1 \\
\times & 1 & 0 & 1 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
\end{array}
\]

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Example: Multiplying Two Integers

Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 \\
1 & 0 & 0 & 1 \\
\end{array}
\times
\begin{array}{c}
1 \\
0 \\
1 \\
1 \\
\end{array}
\]

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 \\
\end{array}
\]

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\[
\begin{array}{cccc}
1 & 0 & 0 & 0 & 1 \\
\times & 1 & 0 & 1 & 1 \\
\hline
& 1 & 0 & 0 & 0 & 1
\end{array}
\]

This is also known as the “school method” for multiplying integers.

Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.
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Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 \\
\times & 1 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
\hline
1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 \\
\end{array}
\]

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- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.
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Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 & 1 \\
\times & 1 & 0 & 1 & 1
\end{array}
\]

\[
\begin{array}{ccccccc}
1 & 0 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
\hline
1 & 0 & 1 & 1 & 1 & 0 & 1 & 1
\end{array}
\]

• This is also known as the “school method” for multiplying integers.
• Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.

Time requirement:
Example: Multiplying Two Integers

Suppose that we want to multiply an \( n \)-bit integer \( A \) and an \( m \)-bit integer \( B \) \((m \leq n)\).

\[
\begin{array}{cccc}
1 & 0 & 0 & 0 \\
\times & 1 & 0 & 1 \\
\hline
1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 \\
1 & 0 & 1 & 1 \\
\end{array}
\]

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most \( m + n \leq 2n \) bits.

Time requirement:
- Computing intermediate results: \( O(nm) \).
Example: Multiplying Two Integers

Suppose that we want to multiply an $n$-bit integer $A$ and an $m$-bit integer $B$ ($m \leq n$).

\[
\begin{array}{c}
1 & 0 & 0 & 0 & 1 \\
\times & & & & 1 & 0 & 1 & 1 \\
\hline
1 & 0 & 0 & 0 & 1 \\
1 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 \\
1 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\
\hline
1 & 0 & 1 & 1 & 1 & 0 & 1 & 1 \\
\end{array}
\]

- This is also known as the “school method” for multiplying integers.
- Note that the intermediate numbers that are generated can have at most $m + n \leq 2n$ bits.

Time requirement:
- Computing intermediate results: $\Theta(nm)$.
- Adding $m$ numbers of length $\leq 2n$: $\Theta((m + n)m) = \Theta(nm)$. 
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$. 
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$. 

![Diagram illustrating multiplication of integers A and B]

Then it holds that $A = A_1 \cdot 2^{n/2} + A_0$ and $B = B_1 \cdot 2^{n/2} + B_0$.

Hence, $A \times B = A_1B_1 \cdot 2^{n/2} + (A_1B_0 + A_0B_1) \cdot 2^{n/2} + A_0B_0$. 

6.2 Master Theorem
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$.

$$A \times B = \begin{array}{c} b_{n-1} \cdots b_0 \\ \end{array} \times \begin{array}{c} a_{n-1} \cdots a_0 \\ \end{array}$$
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$.

$\begin{array}{c}
\vdots \\
b_{n-1} & \cdots & b_{n/2} & b_{n/2-1} & \cdots & b_0 \\
\end{array}$
$\times$
$\begin{array}{c}
\vdots \\
a_{n-1} & \cdots & a_{n/2} & a_{n/2-1} & \cdots & a_0 \\
\end{array}$
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$. 

\[
\begin{array}{c}
B_1 \\
B_0 \\
\end{array} \times
\begin{array}{c}
A_1 \\
A_0 \\
\end{array}
\]
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$.

\[
\begin{array}{cc}
  B_1 & B_0 \\
  \times \\
  A_1 & A_0
\end{array}
\]

Then it holds that

\[
A = A_1 \cdot 2^{\frac{n}{2}} + A_0 \quad \text{and} \quad B = B_1 \cdot 2^{\frac{n}{2}} + B_0
\]
Example: Multiplying Two Integers

A recursive approach:
Suppose that integers $A$ and $B$ are of length $n = 2^k$, for some $k$.

Then it holds that

$$A = A_1 \cdot 2^{\frac{n}{2}} + A_0 \text{ and } B = B_1 \cdot 2^{\frac{n}{2}} + B_0$$

Hence,

$$A \cdot B = A_1 B_1 \cdot 2^n + (A_1 B_0 + A_0 B_1) \cdot 2^{\frac{n}{2}} + A_0 B_0$$
Algorithm 3 $\text{mult}(A, B)$

1: if $|A| = |B| = 1$ then
2: \hspace{1em} return $a_0 \cdot b_0$
3: split $A$ into $A_0$ and $A_1$
4: split $B$ into $B_0$ and $B_1$
5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$
6: $Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)$
7: $Z_0 \leftarrow \text{mult}(A_0, B_0)$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

We get the following recurrence:

$$T(n) = 4 \cdot T\left(\frac{n}{2}\right) + O(n).$$
Example: Multiplying Two Integers

Algorithm 3 \text{mult}(A,B)

1: \textbf{if} \ |A| = |B| = 1 \textbf{then}
2: \quad \textbf{return} \ a_0 \cdot b_0
3: \quad \text{split} \ A \text{ into} \ A_0 \text{ and} \ A_1
4: \quad \text{split} \ B \text{ into} \ B_0 \text{ and} \ B_1
5: \quad Z_2 \leftarrow \text{mult}(A_1, B_1)
6: \quad Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)
7: \quad Z_0 \leftarrow \text{mult}(A_0, B_0)
8: \textbf{return} \ Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0

\Theta(1)
Example: Multiplying Two Integers

**Algorithm 3 mult**(A, B)

1:  **if** |A| = |B| = 1 **then**
2:    **return** a₀ · b₀
3:  split A into A₀ and A₁
4:  split B into B₀ and B₁
5:  Z₂ ← mult(A₁, B₁)
6:  Z₁ ← mult(A₁, B₀) + mult(A₀, B₁)
7:  Z₀ ← mult(A₀, B₀)
8:  **return** Z₂ · 2^n + Z₁ · 2^{n/2} + Z₀

We get the following recurrence:

\[ T(n) = 4T\left(\frac{n}{2}\right) + O(n) \]
Algorithm 3 mult\((A,B)\)

1: if \(|A| = |B| = 1\) then
2: \(\text{return } a_0 \cdot b_0\)
3: split \(A\) into \(A_0\) and \(A_1\)
4: split \(B\) into \(B_0\) and \(B_1\)
5: \(Z_2 \leftarrow \text{mult}(A_1, B_1)\)
6: \(Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)\)
7: \(Z_0 \leftarrow \text{mult}(A_0, B_0)\)
8: \(\text{return } Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0\)

\(O(1)\)
\(O(1)\)
\(O(n)\)
Example: Multiplying Two Integers

Algorithm 3 mult($A, B$)

1: if $|A| = |B| = 1$ then
2: return $a_0 \cdot b_0$
3: split $A$ into $A_0$ and $A_1$
4: split $B$ into $B_0$ and $B_1$
5: $Z_2 \leftarrow$ mult($A_1, B_1$)
6: $Z_1 \leftarrow$ mult($A_1, B_0$) + mult($A_0, B_1$)
7: $Z_0 \leftarrow$ mult($A_0, B_0$)
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

$O(1)$

$O(1)$

$O(n)$

$O(n)$

We get the following recurrence:

$T(n) = 4T\left(\frac{n}{2}\right) + O(n).$
Example: Multiplying Two Integers

Algorithm 3 mult(A, B)

1: if |A| = |B| = 1 then
2: return a₀ · b₀
3: split A into A₀ and A₁
4: split B into B₀ and B₁
5: Z₂ ← mult(A₁, B₁)
6: Z₁ ← mult(A₁, B₀) + mult(A₀, B₁)
7: Z₀ ← mult(A₀, B₀)
8: return Z₂ · 2ⁿ + Z₁ · 2ⁿ/2 + Z₀

Ω(1) Ω(1) Ω(1) Ω(n) Ω(n) T(n/2)

We get the following recurrence:

T(n) = 4T(n/2) + Ω(n)
Example: Multiplying Two Integers

Algorithm 3 \( \text{mult}(A, B) \)

1: if \( |A| = |B| = 1 \) then

2: return \( a_0 \cdot b_0 \)

3: split \( A \) into \( A_0 \) and \( A_1 \)

4: split \( B \) into \( B_0 \) and \( B_1 \)

5: \( Z_2 \leftarrow \text{mult}(A_1, B_1) \)

6: \( Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1) \)

7: \( Z_0 \leftarrow \text{mult}(A_0, B_0) \)

8: return \( Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0 \)

\( \mathcal{O}(1) \)

\( \mathcal{O}(1) \)

\( \mathcal{O}(n) \)

\( \mathcal{O}(n) \)

\( T(\frac{n}{2}) \)

\( 2T(\frac{n}{2}) + \mathcal{O}(n) \)
Algorithm 3 $\text{mult}(A, B)$

1: if $|A| = |B| = 1$ then
2:     return $a_0 \cdot b_0$
3: split $A$ into $A_0$ and $A_1$
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6: $Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)$
7: $Z_0 \leftarrow \text{mult}(A_0, B_0)$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

We get the following recurrence:

$$T(n) = 4T\left(\frac{n}{2}\right) + O(n)$$
Example: Multiplying Two Integers

Algorithm 3 $\text{mult}(A, B)$

1: if $|A| = |B| = 1$ then
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6: $Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1)$
7: $Z_0 \leftarrow \text{mult}(A_0, B_0)$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

$O(1)$

$O(1)$

$O(n)$

$O(n)$

$T(\frac{n}{2})$

$2T(\frac{n}{2}) + O(n)$

$T(\frac{n}{2})$

$O(n)$
Example: Multiplying Two Integers

Algorithm 3 \text{mult}(A, B)

1: \textbf{if} \ |A| = |B| = 1 \textbf{then} \quad \mathcal{O}(1)
2: \quad \textbf{return} \ a_0 \cdot b_0 \quad \mathcal{O}(1)
3: \quad \text{split} \ A \ \text{into} \ A_0 \ \text{and} \ A_1 \quad \mathcal{O}(n)
4: \quad \text{split} \ B \ \text{into} \ B_0 \ \text{and} \ B_1 \quad \mathcal{O}(n)
5: \quad Z_2 \leftarrow \text{mult}(A_1, B_1) \quad T(\frac{n}{2})
6: \quad Z_1 \leftarrow \text{mult}(A_1, B_0) + \text{mult}(A_0, B_1) \quad 2T(\frac{n}{2}) + \mathcal{O}(n)
7: \quad Z_0 \leftarrow \text{mult}(A_0, B_0) \quad T(\frac{n}{2})
8: \quad \textbf{return} \ Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0 \quad \mathcal{O}(n)

We get the following recurrence:

\[ T(n) = 4T\left(\frac{n}{2}\right) + \mathcal{O}(n) \]
Master Theorem: Recurrence: \( T[n] = aT\left(\frac{n}{b}\right) + f(n) \).

- **Case 1:** \( f(n) = \Theta(n^{\log_b a - \epsilon}) \) \( T(n) = \Theta(n^{\log_b a}) \)
- **Case 2:** \( f(n) = \Theta(n^{\log_b a \log^k n}) \) \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
- **Case 3:** \( f(n) = \Omega(n^{\log_b a + \epsilon}) \) \( T(n) = \Theta(f(n)) \)
Example: Multiplying Two Integers

Master Theorem: Recurrence: \( T[n] = aT\left(\frac{n}{b}\right) + f(n) \).

- **Case 1:** \( f(n) = \Theta(n^{\log_b a - \epsilon}) \) \( T(n) = \Theta(n^{\log_b a}) \)
- **Case 2:** \( f(n) = \Theta(n^{\log_b a \log^k n}) \) \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
- **Case 3:** \( f(n) = \Omega(n^{\log_b a + \epsilon}) \) \( T(n) = \Theta(f(n)) \)

In our case \( a = 4, \ b = 2, \) and \( f(n) = \Theta(n) \). Hence, we are in Case 1, since \( n = \Theta(n^{2-\epsilon}) = \Theta(n^{\log_b a - \epsilon}) \).
**Example: Multiplying Two Integers**

**Master Theorem:** Recurrence: \( T[n] = aT\left(\frac{n}{b}\right) + f(n) \).

- **Case 1:** \( f(n) = O(n^{\log_b a - \epsilon}) \)  \( T(n) = \Theta(n^{\log_b a}) \)
- **Case 2:** \( f(n) = \Theta(n^{\log_b a \log^k n}) \)  \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
- **Case 3:** \( f(n) = \Omega(n^{\log_b a + \epsilon}) \)  \( T(n) = \Theta(f(n)) \)

In our case \( a = 4, b = 2, \) and \( f(n) = \Theta(n) \). Hence, we are in Case 1, since  \( n = O(n^{2-\epsilon}) = O(n^{\log_b a - \epsilon}) \).

We get a running time of \( O(n^2) \) for our algorithm.
Example: Multiplying Two Integers

**Master Theorem:** Recurrence: \( T[n] = aT\left(\frac{n}{b}\right) + f(n). \)

- **Case 1:** \( f(n) = O(n^{\log_b a - \epsilon}) \)  
  \( T(n) = \Theta(n^{\log_b a}) \)

- **Case 2:** \( f(n) = \Theta(n^{\log_b a} \log^k n) \)  
  \( T(n) = \Theta(n^{\log_b a} \log^{k+1} n) \)

- **Case 3:** \( f(n) = \Omega(n^{\log_b a + \epsilon}) \)  
  \( T(n) = \Theta(f(n)) \)

In our case \( a = 4, \ b = 2, \) and \( f(n) = \Theta(n). \) Hence, we are in Case 1, since \( n = O(n^{2-\epsilon}) = O(n^{\log_b a - \epsilon}). \)

We get a running time of \( O(n^2) \) for our algorithm.

\( \Rightarrow \) Not better then the “school method”.
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1 B_0 + A_0 B_1 = (A_0 + A_1) \cdot (B_0 + B_1) - A_1 B_1 - A_0 B_0$$

Hence, Algorithm 4

```pseudocode
mult(A, B)
1: if |A| = |B| = 1 then
2: return $a_0 \cdot b_0$
3: split $A$ into $A_0$ and $A_1$
4: split $B$ into $B_0$ and $B_1$
5: $Z_2 \leftarrow mult(A_1, B_1)$
6: $Z_0 \leftarrow mult(A_0, B_0)$
7: $Z_1 \leftarrow mult(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^n + Z_0$
```

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + \Theta(n)$. 
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1 B_0 + A_0 B_1$$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T\left(\frac{n}{2} + 1\right) + \mathcal{O}(n)$. 
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1 B_0 + A_0 B_1$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1 B_1 - A_0 B_0$$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + \mathcal{O}(n)$. 
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T\left(\frac{n}{2} + 1\right) + O(n)$. 

6.2 Master Theorem
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

\[
Z_1 = A_1 B_0 + A_0 B_1 = Z_2 = Z_0
\]

\[
= (A_0 + A_1) \cdot (B_0 + B_1) - A_1 B_1 - A_0 B_0
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Hence,

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + O(n)$. 

6.2 Master Theorem
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0 = (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

```
Algorithm 4 mult(A, B)
1: if |A| = |B| = 1 then
2:   return $a_0 \cdot b_0$
3: split A into $A_0$ and $A_1$
4: split B into $B_0$ and $B_1$
5: $Z_2 \leftarrow$ mult($A_1, B_1$)
6: $Z_0 \leftarrow$ mult($A_0, B_0$)
7: $Z_1 \leftarrow$ mult($A_0 + A_1, B_0 + B_1$) − $Z_2 − Z_0$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$
```

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + O(n)$. 
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

Algorithm 4 $\text{mult}(A, B)$

1: if $|A| = |B| = 1$ then
2: return $a_0 \cdot b_0$
3: split $A$ into $A_0$ and $A_1$
4: split $B$ into $B_0$ and $B_1$
5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$
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7: $Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + O(n)$. 

$O(1)$
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

Algorithm 4 mult$(A, B)$

1: if $|A| = |B| = 1$ then
2: return $a_0 \cdot b_0$
3: split $A$ into $A_0$ and $A_1$
4: split $B$ into $B_0$ and $B_1$
5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$
6: $Z_0 \leftarrow \text{mult}(A_0, B_0)$
7: $Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^\frac{n}{2} + Z_0$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + O(n)$. 

$O(1)$
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1 B_0 + A_0 B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1 B_1 - A_0 B_0$$

Hence,

```
Algorithm 4 mult(A, B)
1: if |A| = |B| = 1 then
2:   return $a_0 \cdot b_0$
3: split A into $A_0$ and $A_1$
4: split B into $B_0$ and $B_1$
5: $Z_2 \leftarrow$ mult($A_1, B_1$)
6: $Z_0 \leftarrow$ mult($A_0, B_0$)
7: $Z_1 \leftarrow$ mult($A_0 + A_1, B_0 + B_1$) - $Z_2 - Z_0$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$
```

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + O(n)$.  

6.2 Master Theorem

Ernst Mayr, Harald Räcke
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1 B_0 + A_0 B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1 B_1 - A_0 B_0$$

Hence,

<table>
<thead>
<tr>
<th>Algorithm 4 $\text{mult}(A, B)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: if $</td>
</tr>
<tr>
<td>2: return $a_0 \cdot b_0$</td>
</tr>
<tr>
<td>3: split $A$ into $A_0$ and $A_1$</td>
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<tr>
<td>8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{\frac{n}{2}} + Z_0$</td>
</tr>
</tbody>
</table>

A more precise (correct) analysis would say that computing $Z_1$ needs time $T\left(\frac{n}{2} + 1\right) + O(n)$. 

$O(1)$ $O(1)$ $O(n)$ $O(n)$
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

**Algorithm 4** \texttt{mult}(A, B)

1: \textbf{if} $|A| = |B| = 1$ \textbf{then} $\mathcal{O}(1)$
2: \textbf{return} $a_0 \cdot b_0$ $\mathcal{O}(1)$
3: split $A$ into $A_0$ and $A_1$ $\mathcal{O}(n)$
4: split $B$ into $B_0$ and $B_1$ $\mathcal{O}(n)$
5: $Z_2 \leftarrow \text{mult}(A_1, B_1)$ $T\left(\frac{n}{2}\right)$
6: $Z_0 \leftarrow \text{mult}(A_0, B_0)$
7: $Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0$
8: \textbf{return} $Z_2 \cdot 2^n + Z_1 \cdot 2^n + Z_0$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T\left(\frac{n}{2} + 1\right) + \mathcal{O}(n)$.  

6.2 Master Theorem 11. Apr. 2018
Ernst Mayr, Harald Räcke
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$
$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

```
Algorithm 4 mult(A, B)
1: if |A| = |B| = 1 then
2: return $a_0 \cdot b_0$
3: split A into $A_0$ and $A_1$
4: split B into $B_0$ and $B_1$
5: $Z_2 \leftarrow$ mult($A_1, B_1$)
6: $Z_0 \leftarrow$ mult($A_0, B_0$)
7: $Z_1 \leftarrow$ mult($A_0 + A_1, B_0 + B_1$) $- Z_2 - Z_0$
8: return $Z_2 \cdot 2^n + Z_1 \cdot 2^{n/2} + Z_0$
```

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + \mathcal{O}(n)$.  

$\mathcal{O}(1)$ $\mathcal{O}(1)$ $\mathcal{O}(n)$ $\mathcal{O}(n)$ $T(\frac{n}{2})$ $T(\frac{n}{2})$
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

Algorithm 4 \text{mult}(A, B)


1: \textbf{if } |A| = |B| = 1 \textbf{ then} \quad \mathcal{O}(1)

2: \textbf{return } a_0 \cdot b_0 \quad \mathcal{O}(1)

3: \text{split } A \text{ into } A_0 \text{ and } A_1 \quad \mathcal{O}(n)

4: \text{split } B \text{ into } B_0 \text{ and } B_1 \quad \mathcal{O}(n)

5: Z_2 \leftarrow \text{mult}(A_1, B_1) \quad T\left(\frac{n}{2}\right)

6: Z_0 \leftarrow \text{mult}(A_0, B_0) \quad T\left(\frac{n}{2}\right)

7: Z_1 \leftarrow \text{mult}(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0 \quad T\left(\frac{n}{2}\right) + \mathcal{O}(n)

8: \textbf{return } Z_2 \cdot 2^n + Z_1 \cdot 2^n + Z_0 \quad T\left(\frac{n}{2}\right) + \mathcal{O}(n)$

A more precise (correct) analysis would say that computing $Z_1$ needs time $T\left(\frac{n}{2} + 1\right) + \mathcal{O}(n)$. 
Example: Multiplying Two Integers

We can use the following identity to compute $Z_1$:

$$Z_1 = A_1B_0 + A_0B_1 = Z_2 = Z_0$$

$$= (A_0 + A_1) \cdot (B_0 + B_1) - A_1B_1 - A_0B_0$$

Hence,

```
Algorithm 4 mult(A, B)
1: if |A| = |B| = 1 then
2:    return a_0 \cdot b_0
3: split A into A_0 and A_1
4: split B into B_0 and B_1
5: Z_2 \leftarrow mult(A_1, B_1)
6: Z_0 \leftarrow mult(A_0, B_0)
7: Z_1 \leftarrow mult(A_0 + A_1, B_0 + B_1) - Z_2 - Z_0
8: return Z_2 \cdot 2^n + Z_1 \cdot 2^{n/2} + Z_0
```

A more precise (correct) analysis would say that computing $Z_1$ needs time $T(\frac{n}{2} + 1) + \mathcal{O}(n)$.

6.2 Master Theorem
Example: Multiplying Two Integers

We get the following recurrence:

\[ T(n) = 3T\left(\frac{n}{2}\right) + O(n) . \]

Master Theorem: Recurrence: \[ T[n] = aT\left(\frac{n}{b}\right) + f(n). \]

- Case 1: \( f(n) = O(n^{\log_b a - \epsilon}) \) \( T(n) = \Theta(n^{\log_b a}) \)
- Case 2: \( f(n) = \Theta(n^{\log_b a \log^k \log n}) \) \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
- Case 3: \( f(n) = \Omega(n^{\log_b a + \epsilon}) \) \( T(n) = \Theta(f(n)) \)

Again we are in Case 1. We get a running time of
\( \Theta(n^{\log_2 3}) \approx \Theta(n^{1.59}) \).

A huge improvement over the “school method”.
Example: Multiplying Two Integers

We get the following recurrence:

\[ T(n) = 3T\left(\frac{n}{2}\right) + \mathcal{O}(n) \, . \]

Master Theorem: Recurrence: \( T[n] = aT\left(\frac{n}{b}\right) + f(n) \).

- **Case 1:** \( f(n) = \mathcal{O}(n^{\log_b a - \epsilon}) \) \( T(n) = \Theta(n^{\log_b a}) \)
- **Case 2:** \( f(n) = \Theta(n^{\log_b a \log^k n}) \) \( T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
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6.2 Master Theorem
Example: Multiplying Two Integers

We get the following recurrence:

\[ T(n) = 3T\left(\frac{n}{2}\right) + \Theta(n) \, . \]

Master Theorem: Recurrence: \( T[n] = aT(\frac{n}{b}) + f(n). \)

- **Case 1:** \( f(n) = \Theta(n^{\log_b a - \epsilon}) \quad T(n) = \Theta(n^{\log_b a}) \)
- **Case 2:** \( f(n) = \Theta(n^{\log_b a \log^k n}) \quad T(n) = \Theta(n^{\log_b a \log^{k+1} n}) \)
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Again we are in Case 1. We get a running time of \( \Theta(n^{\log_2 3}) \approx \Theta(n^{1.59}). \)

A huge improvement over the “school method”.
Consider the recurrence relation:

\[ c_0 T(n) + c_1 T(n - 1) + c_2 T(n - 2) + \cdots + c_k T(n - k) = f(n) \]

This is the general form of a linear recurrence relation of order \( k \) with constant coefficients \((c_0, c_k \neq 0)\).

- This only depends on the \( k \) preceding values. This means the recurrence relation is of order \( k \).
- The recurrence is linear as there are no products of \( T[n]'s \).
- If \( f(n) = 0 \) then the recurrence relation becomes a linear, homogenous recurrence relation of order \( k \).

Note that we ignore boundary conditions for the moment.
6.3 The Characteristic Polynomial

Consider the recurrence relation:

\[ c_0 T(n) + c_1 T(n - 1) + c_2 T(n - 2) + \cdots + c_k T(n - k) = f(n) \]

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Note that we ignore boundary conditions for the moment.
6.3 The Characteristic Polynomial

Observations:

- The solution $T[1], T[2], T[3], \ldots$ is completely determined by a set of boundary conditions that specify values for $T[1], \ldots, T[k]$.
- In fact, any $k$ consecutive values completely determine the solution.
- $k$ non-consecutive values might not be an appropriate set of boundary conditions (depends on the problem).

Approach:

- First determine all solutions that satisfy recurrence relation.
- Then pick the right one by analyzing boundary conditions.
- First consider the homogenous case.
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The Homogenous Case

The solution space

\[ S = \{ T = T[1], T[2], T[3], \ldots \mid T \text{ fulfills recurrence relation} \} \]

is a vector space. This means that if \( T_1, T_2 \in S \), then also \( \alpha T_1 + \beta T_2 \in S \), for arbitrary constants \( \alpha, \beta \).

How do we find a non-trivial solution?

We guess that the solution is of the form \( \lambda^n, \lambda \neq 0 \), and see what happens. In order for this guess to fulfill the recurrence we need

\[
c_0 \lambda^n + c_1 \lambda^{n-1} + c_2 \cdot \lambda^{n-2} + \cdots + c_k \cdot \lambda^{n-k} = 0
\]

for all \( n \geq k \).
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\[ c_0 \lambda^n + c_1 \lambda^{n-1} + c_2 \lambda^{n-2} + \cdots + c_k \lambda^{n-k} = 0 \]

for all \( n \geq k \).
The Homogenous Case

Dividing by $\lambda^{n-k}$ gives that all these constraints are identical to

$$c_0\lambda^k + c_1\lambda^{k-1} + c_2 \cdot \lambda^{k-2} + \cdots + c_k = 0$$

This means that if $\lambda_i$ is a root (Nullstelle) of $P[\lambda]$ then $T[n] = \lambda_i^n$ is a solution to the recurrence relation.

Let $\lambda_1, \ldots, \lambda_k$ be the $k$ (complex) roots of $P[\lambda]$. Then, because of the vector space property

$$\alpha_1\lambda_1^n + \alpha_2\lambda_2^n + \cdots + \alpha_k\lambda_k^n$$

is a solution for arbitrary values $\alpha_i$. 
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6.3 The Characteristic Polynomial
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The Homogenous Case

Lemma 5

Assume that the characteristic polynomial has \( k \) distinct roots \( \lambda_1, \ldots, \lambda_k \). Then all solutions to the recurrence relation are of the form

\[
\alpha_1 \lambda_1^n + \alpha_2 \lambda_2^n + \cdots + \alpha_k \lambda_k^n.
\]

Proof.

There is one solution for every possible choice of boundary conditions for \( T[1], \ldots, T[k] \).

We show that the above set of solutions contains one solution for every choice of boundary conditions.
 Lemma 5
Assume that the characteristic polynomial has \( k \) distinct roots \( \lambda_1, \ldots, \lambda_k \). Then all solutions to the recurrence relation are of the form
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The Homogenous Case

Lemma 5
Assume that the characteristic polynomial has $k$ distinct roots $\lambda_1, \ldots, \lambda_k$. Then all solutions to the recurrence relation are of the form

$$\alpha_1 \lambda_1^n + \alpha_2 \lambda_2^n + \cdots + \alpha_k \lambda_k^n.$$ 

Proof.
There is one solution for every possible choice of boundary conditions for $T[1], \ldots, T[k]$.

We show that the above set of solutions contains one solution for every choice of boundary conditions.
The Homogenous Case

Proof (cont.).

Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha_i'$s such that these conditions are met:
The Homogenous Case

Proof (cont.).

Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha'_i$s such that these conditions are met:

$$\alpha_1 \cdot \lambda_1 + \alpha_2 \cdot \lambda_2 + \cdots + \alpha_k \cdot \lambda_k = T[1]$$
The Homogenous Case

Proof (cont.).
Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha_i's$ such that these conditions are met:

\[
\begin{align*}
\alpha_1 \cdot \lambda_1 &+ \alpha_2 \cdot \lambda_2 + \cdots + \alpha_k \cdot \lambda_k = T[1] \\
\alpha_1 \cdot \lambda_1^2 &+ \alpha_2 \cdot \lambda_2^2 + \cdots + \alpha_k \cdot \lambda_k^2 = T[2]
\end{align*}
\]
The Homogenous Case

Proof (cont.).

Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha'_i$s such that these conditions are met:

\begin{align*}
\alpha_1 \cdot \lambda_1 &+ \alpha_2 \cdot \lambda_2 + \cdots + \alpha_k \cdot \lambda_k = T[1] \\
\alpha_1 \cdot \lambda_1^2 &+ \alpha_2 \cdot \lambda_2^2 + \cdots + \alpha_k \cdot \lambda_k^2 = T[2] \\
\vdots
\end{align*}
The Homogenous Case

Proof (cont.).
Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha'_i$s such that these conditions are met:

\[
\alpha_1 \cdot \lambda_1 + \alpha_2 \cdot \lambda_2 + \cdots + \alpha_k \cdot \lambda_k = T[1] \\
\alpha_1 \cdot \lambda_1^2 + \alpha_2 \cdot \lambda_2^2 + \cdots + \alpha_k \cdot \lambda_k^2 = T[2] \\
\vdots \\
\alpha_1 \cdot \lambda_1^k + \alpha_2 \cdot \lambda_2^k + \cdots + \alpha_k \cdot \lambda_k^k = T[k]
\]
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Proof (cont.).

Suppose I am given boundary conditions $T[i]$ and I want to see whether I can choose the $\alpha_i's$ such that these conditions are met:

$$
\begin{pmatrix}
\lambda_1 & \lambda_2 & \ldots & \lambda_k \\
\lambda_1^2 & \lambda_2^2 & \ldots & \lambda_k^2 \\
\vdots & & & \\
\lambda_1^k & \lambda_2^k & \ldots & \lambda_k^k
\end{pmatrix}
\begin{pmatrix}
\alpha_1 \\
\alpha_2 \\
\vdots \\
\alpha_k
\end{pmatrix}
= 
\begin{pmatrix}
T[1] \\
T[2] \\
\vdots \\
T[k]
\end{pmatrix}
$$

We show that the column vectors are linearly independent. Then the above equation has a solution.
Proof (cont.).

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$$
\begin{pmatrix}
\lambda_1 & \lambda_2 & \cdots & \lambda_k \\
\lambda_1^2 & \lambda_2^2 & \cdots & \lambda_k^2 \\
\vdots & & & \\
\lambda_1^k & \lambda_2^k & \cdots & \lambda_k^k \\
\end{pmatrix}
\begin{pmatrix}
\alpha_1 \\
\alpha_2 \\
\vdots \\
\alpha_k \\
\end{pmatrix}
= 
\begin{pmatrix}
T[1] \\
T[2] \\
\vdots \\
T[k] \\
\end{pmatrix}
$$

We show that the column vectors are linearly independent. Then the above equation has a solution.
Computing the Determinant

\[
\begin{vmatrix}
\lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\
\lambda_1^2 & \lambda_2^2 & \cdots & \lambda_{k-1}^2 & \lambda_k^2 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\lambda_1^k & \lambda_2^k & \cdots & \lambda_{k-1}^k & \lambda_k^k \\
\end{vmatrix} = \prod_{i=1}^{k} \lambda_i
\]
Computing the Determinant

\[
\begin{vmatrix}
\lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\
\lambda_1^2 & \lambda_2^2 & \cdots & \lambda_{k-1}^2 & \lambda_k^2 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\lambda_1^k & \lambda_2^k & \cdots & \lambda_{k-1}^k & \lambda_k^k \\
\end{vmatrix} = \prod_{i=1}^{k} \lambda_i \cdot \begin{vmatrix}
1 & 1 & \cdots & 1 & 1 \\
\lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\lambda_1^{k-1} & \lambda_2^{k-1} & \cdots & \lambda_{k-1}^{k-1} & \lambda_k^{k-1} \\
\end{vmatrix}
\]
Computing the Determinant

\[
\begin{vmatrix}
\lambda_1 & \lambda_2 & \ldots & \lambda_{k-1} & \lambda_k \\
\lambda_2 & \lambda_2 & \ldots & \lambda_{k-1}^2 & \lambda_k^2 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\lambda_k & \lambda_k & \ldots & \lambda_{k-1}^k & \lambda_k^k
\end{vmatrix}
= \prod_{i=1}^{k} \lambda_i 
\]

\[
\begin{vmatrix}
1 & 1 & \ldots & 1 & 1 \\
\lambda_1 & \lambda_2 & \ldots & \lambda_{k-1} & \lambda_k \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\lambda_{k-1} & \lambda_{k-1} & \ldots & \lambda_{k-1}^{k-1} & \lambda_{k-1}^{k-1}
\end{vmatrix}
= \prod_{i=1}^{k} \lambda_i 
\]

\[
\begin{vmatrix}
1 & \lambda_1 & \ldots & \lambda_1^{k-2} & \lambda_1^{k-1} \\
1 & \lambda_2 & \ldots & \lambda_2^{k-2} & \lambda_2^{k-1} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k & \ldots & \lambda_k^{k-2} & \lambda_k^{k-1}
\end{vmatrix}
\]

6.3 The Characteristic Polynomial

Ernst Mayr, Harald Räcke
Computing the Determinant

\[
\begin{vmatrix}
1 & \lambda_1 & \ldots & \lambda_1^{k-2} & \lambda_1^{k-1} \\
1 & \lambda_2 & \ldots & \lambda_2^{k-2} & \lambda_2^{k-1} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k & \ldots & \lambda_k^{k-2} & \lambda_k^{k-1}
\end{vmatrix} =
\]
Computing the Determinant

\[
\begin{vmatrix}
1 & \lambda_1 & \cdots & \lambda_1^{k-2} & \lambda_1^{k-1} \\
1 & \lambda_2 & \cdots & \lambda_2^{k-2} & \lambda_2^{k-1} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k & \cdots & \lambda_k^{k-2} & \lambda_k^{k-1}
\end{vmatrix}
= \\
\begin{vmatrix}
1 & \lambda_1 - \lambda_1 \cdot 1 & \cdots & \lambda_1^{k-2} - \lambda_1 \cdot \lambda_1^{k-3} & \lambda_1^{k-1} - \lambda_1 \cdot \lambda_1^{k-2} \\
1 & \lambda_2 - \lambda_1 \cdot 1 & \cdots & \lambda_2^{k-2} - \lambda_1 \cdot \lambda_2^{k-3} & \lambda_2^{k-1} - \lambda_1 \cdot \lambda_2^{k-2} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k - \lambda_1 \cdot 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2}
\end{vmatrix}
\]
Computing the Determinant

\[
\begin{vmatrix}
1 & \lambda_1 - \lambda_1 \cdot 1 & \cdots & \lambda_1^{k-2} - \lambda_1 \cdot \lambda_1^{k-3} & \lambda_1^{k-1} - \lambda_1 \cdot \lambda_1^{k-2} \\
1 & \lambda_2 - \lambda_1 \cdot 1 & \cdots & \lambda_2^{k-2} - \lambda_1 \cdot \lambda_2^{k-3} & \lambda_2^{k-1} - \lambda_1 \cdot \lambda_2^{k-2} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k - \lambda_1 \cdot 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2}
\end{vmatrix} =
\]
Computing the Determinant

\[
\begin{vmatrix}
1 & \lambda_1 - \lambda_1 \cdot 1 & \cdots & \lambda_1^{k-2} - \lambda_1 \cdot \lambda_1^{k-3} & \lambda_1^{k-1} - \lambda_1 \cdot \lambda_1^{k-2} \\
1 & \lambda_2 - \lambda_1 \cdot 1 & \cdots & \lambda_2^{k-2} - \lambda_1 \cdot \lambda_2^{k-3} & \lambda_2^{k-1} - \lambda_1 \cdot \lambda_2^{k-2} \\
\vdots & \vdots & \cdots & \vdots & \vdots \\
1 & \lambda_k - \lambda_1 \cdot 1 & \cdots & \lambda_k^{k-2} - \lambda_1 \cdot \lambda_k^{k-3} & \lambda_k^{k-1} - \lambda_1 \cdot \lambda_k^{k-2} \\
\end{vmatrix} = \\
\begin{vmatrix}
1 & 0 & \cdots & 0 & 0 \\
1 & (\lambda_2 - \lambda_1) \cdot 1 & \cdots & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-3} & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-2} \\
\vdots & \vdots & \cdots & \vdots & \vdots \\
1 & (\lambda_k - \lambda_1) \cdot 1 & \cdots & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-3} & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-2} \\
\end{vmatrix}
\]
Computing the Determinant

\[
\begin{vmatrix}
1 & 0 & \cdots & 0 & 0 \\
1 & (\lambda_2 - \lambda_1) \cdot 1 & \cdots & (\lambda_2 - \lambda_1) \cdot \lambda^{k-3}_2 & (\lambda_2 - \lambda_1) \cdot \lambda^{k-2}_2 \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & (\lambda_k - \lambda_1) \cdot 1 & \cdots & (\lambda_k - \lambda_1) \cdot \lambda^{k-3}_k & (\lambda_k - \lambda_1) \cdot \lambda^{k-2}_k
\end{vmatrix} =
\]
Computing the Determinant

\[
\begin{vmatrix}
1 & 0 & \cdots & 0 \\
1 & (\lambda_2 - \lambda_1) \cdot 1 & \cdots & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-3} & (\lambda_2 - \lambda_1) \cdot \lambda_2^{k-2} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & (\lambda_k - \lambda_1) \cdot 1 & \cdots & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-3} & (\lambda_k - \lambda_1) \cdot \lambda_k^{k-2}
\end{vmatrix}
\]

\[
\prod_{i=2}^{k} (\lambda_i - \lambda_1) \cdot 
\begin{vmatrix}
1 & \lambda_2 & \cdots & \lambda_2^{k-3} & \lambda_2^{k-2} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
1 & \lambda_k & \cdots & \lambda_k^{k-3} & \lambda_k^{k-2}
\end{vmatrix}
\]
Computing the Determinant

Repeating the above steps gives:

\[
\begin{vmatrix}
\lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\
\lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
\lambda_1 & \lambda_2 & \cdots & \lambda_{k-1} & \lambda_k \\
\end{vmatrix} = \prod_{i=1}^{k} \lambda_i \cdot \prod_{i>\ell} (\lambda_i - \lambda_\ell)
\]

Hence, if all \( \lambda_i \)'s are different, then the determinant is non-zero.
The Homogeneous Case

What happens if the roots are not all distinct?

Suppose we have a root \( \lambda_i \) with multiplicity (Vielfachheit) at least 2. Then not only is \( \lambda_i^n \) a solution to the recurrence but also \( n\lambda_i^n \).

To see this consider the polynomial

\[
P[\lambda] \cdot \lambda^{n-k} = c_0\lambda^n + c_1\lambda^{n-1} + c_2\lambda^{n-2} + \cdots + c_k\lambda^{n-k}
\]

Since \( \lambda_i \) is a root we can write this as \( Q[\lambda] \cdot (\lambda - \lambda_i)^2 \).

Calculating the derivative gives a polynomial that still has root \( \lambda_i \).
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Since $\lambda_i$ is a root we can write this as $Q[\lambda] \cdot (\lambda - \lambda_i)^2$. Calculating the derivative gives a polynomial that still has root $\lambda_i$. 
This means

\[ c_0 n \lambda_i^{n-1} + c_1 (n - 1) \lambda_i^{n-2} + \cdots + c_k (n - k) \lambda_i^{n-k-1} = 0 \]

Hence,

\[ \underbrace{c_0 n \lambda_i^n}_{T[n]} + \underbrace{c_1 (n - 1) \lambda_i^{n-1}}_{T[n-1]} + \cdots + \underbrace{c_k (n - k) \lambda_i^{n-k}}_{T[n-k]} = 0 \]
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The Homogeneous Case

Suppose \( \lambda_i \) has multiplicity \( j \). We know that

\[
c_0 n \lambda_i^n + c_1 (n-1) \lambda_i^{n-1} + \cdots + c_k (n-k) \lambda_i^{n-k} = 0
\]

(after taking the derivative; multiplying with \( \lambda \); plugging in \( \lambda_i \))

Doing this again gives

\[
c_0 n^2 \lambda_i^n + c_1 (n-1)^2 \lambda_i^{n-1} + \cdots + c_k (n-k)^2 \lambda_i^{n-k} = 0
\]

We can continue \( j - 1 \) times.

Hence, \( n^\ell \lambda_i^n \) is a solution for \( \ell \in 0, \ldots, j - 1 \).
The Homogeneous Case

Suppose $\lambda_i$ has multiplicity $j$. We know that

$$c_0 n \lambda_i^n + c_1 (n - 1) \lambda_i^{n-1} + \cdots + c_k (n - k) \lambda_i^{n-k} = 0$$

(after taking the derivative; multiplying with $\lambda$; plugging in $\lambda_i$)

Doing this again gives

$$c_0 n^2 \lambda_i^n + c_1 (n - 1)^2 \lambda_i^{n-1} + \cdots + c_k (n - k)^2 \lambda_i^{n-k} = 0$$

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We can continue $j - 1$ times.

Hence, $n^\ell \lambda_i^n$ is a solution for $\ell \in 0, \ldots, j - 1$. 
The Homogeneous Case

Lemma 6
Let $P[\lambda]$ denote the characteristic polynomial to the recurrence

$$c_0 T[n] + c_1 T[n-1] + \cdots + c_k T[n-k] = 0$$

Let $\lambda_i, i = 1, \ldots, m$ be the (complex) roots of $P[\lambda]$ with multiplicities $\ell_i$. Then the general solution to the recurrence is given by

$$T[n] = \sum_{i=1}^{m} \sum_{j=0}^{\ell_i-1} \alpha_{ij} \cdot (n^j \lambda_i^n) .$$

The full proof is omitted. We have only shown that any choice of $\alpha_{ij}$'s is a solution to the recurrence.
Example: Fibonacci Sequence

\[ T[0] = 0 \]
\[ T[1] = 1 \]
\[ T[n] = T[n - 1] + T[n - 2] \quad \text{for } n \geq 2 \]

The characteristic polynomial is

\[ \lambda^2 - \lambda - 1 \]

Finding the roots, gives

\[ \lambda_{1/2} = \frac{1}{2} \pm \sqrt{\frac{1}{4} + 1} = \frac{1}{2} (1 \pm \sqrt{5}) \]
Example: Fibonacci Sequence

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Example: Fibonacci Sequence

Hence, the solution is of the form

\[ \alpha \left( \frac{1 + \sqrt{5}}{2} \right)^n + \beta \left( \frac{1 - \sqrt{5}}{2} \right)^n \]
Example: Fibonacci Sequence

Hence, the solution is of the form

\[ \alpha \left( \frac{1 + \sqrt{5}}{2} \right)^n + \beta \left( \frac{1 - \sqrt{5}}{2} \right)^n \]

\[ T[0] = 0 \] gives \( \alpha + \beta = 0. \)
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\[ T[0] = 0 \text{ gives } \alpha + \beta = 0. \]

\[ T[1] = 1 \text{ gives } \alpha \left( \frac{1 + \sqrt{5}}{2} \right) + \beta \left( \frac{1 - \sqrt{5}}{2} \right) = 1 \]
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\( T[1] = 1 \) gives

\[ \alpha \left( \frac{1 + \sqrt{5}}{2} \right) + \beta \left( \frac{1 - \sqrt{5}}{2} \right) = 1 \implies \alpha - \beta = \frac{2}{\sqrt{5}} \]
Example: Fibonacci Sequence

Hence, the solution is

\[
\frac{1}{\sqrt{5}} \left[ \left( \frac{1 + \sqrt{5}}{2} \right)^n - \left( \frac{1 - \sqrt{5}}{2} \right)^n \right]
\]
The Inhomogeneous Case

Consider the recurrence relation:

\[ c_0 T(n) + c_1 T(n - 1) + c_2 T(n - 2) + \cdots + c_k T(n - k) = f(n) \]

with \( f(n) \neq 0 \).

While we have a fairly general technique for solving \textbf{homogeneous}, linear recurrence relations the inhomogeneous case is different.
The Inhomogeneous Case

The general solution of the recurrence relation is

\[ T(n) = T_h(n) + T_p(n) , \]

where \( T_h \) is any solution to the homogeneous equation, and \( T_p \) is one particular solution to the inhomogeneous equation.

There is no general method to find a particular solution.
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\[ T(n) = T_h(n) + T_p(n) , \]

where \( T_h \) is any solution to the homogeneous equation, and \( T_p \) is one particular solution to the inhomogeneous equation.

There is no general method to find a particular solution.
The Inhomogeneous Case

Example:

\[ T[n] = T[n - 1] + 1 \quad T[0] = 1 \]

Then,

\[ T[n - 1] = T[n - 2] + 1 \quad (n \geq 2) \]

Subtracting the first from the second equation gives,

\[ T[n] - T[n - 1] = T[n - 1] - T[n - 2] \quad (n \geq 2) \]

or

\[ T[n] = 2T[n - 1] - T[n - 2] \quad (n \geq 2) \]

I get a completely determined recurrence if I add \( T[0] = 1 \) and \( T[1] = 2 \).
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Example: Characteristic polynomial:

\[ \lambda^2 - 2\lambda + 1 = 0 \]
The Inhomogeneous Case

**Example:** Characteristic polynomial:

\[
\lambda^2 - 2\lambda + 1 = 0
\]

\[(\lambda-1)^2\]

Then the solution is of the form

\[T[n] = \alpha_n + \beta n\]

\[T[0] = 1\] gives \(\alpha = 1\).

\[T[1] = 2\] gives \(1 + \beta = 2\) \(\Rightarrow \beta = 1\).
The Inhomogeneous Case

**Example:** Characteristic polynomial:

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\[
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Then the solution is of the form

\[ T[n] = \alpha 1^n + \beta n 1^n = \alpha + \beta n \]

\[ T[0] = 1 \text{ gives } \alpha = 1. \]

\[ T[1] = 2 \text{ gives } 1 + \beta = 2 \implies \beta = 1. \]
The Inhomogeneous Case

If $f(n)$ is a polynomial of degree $r$ this method can be applied $r + 1$ times to obtain a homogeneous equation:

$$T[n] = T[n - 1] + n^2$$

Shift:

$$T[n - 1] = T[n - 2] + (n - 1)^2 = T[n - 2] + n^2 - 2n + 1$$

Difference:


$$T[n] = 2T[n - 1] - T[n - 2] + 2n - 1$$
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Difference:

\[
\]

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If $f(n)$ is a polynomial of degree $r$ this method can be applied $r + 1$ times to obtain a homogeneous equation:

$$T[n] = T[n - 1] + n^2$$

Shift:

$$T[n - 1] = T[n - 2] + (n - 1)^2 = T[n - 2] + n^2 - 2n + 1$$

Difference:


$$T[n] = 2T[n - 1] - T[n - 2] + 2n - 1$$
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Difference:

\[
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\[ T[n] = 3T[n - 1] - 3T[n - 2] + T[n - 3] + 2 \]

and so on...
Definition 7 (Generating Function)

Let \((a_n)_{n \geq 0}\) be a sequence. The corresponding

- generating function (Erzeugendenfunktion) is
  \[
  F(z) := \sum_{n \geq 0} a_n z^n;
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6.4 Generating Functions

There are two different views:

A generating function is a formal power series (formale Potenzreihe).

Then the generating function is an algebraic object.

Let $f = \sum_{n \geq 0} a_n z^n$ and $g = \sum_{n \geq 0} b_n z^n$.

- **Equality:** $f$ and $g$ are equal if $a_n = b_n$ for all $n$.
- **Addition:** $f + g := \sum_{n \geq 0} (a_n + b_n) z^n$.
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The arithmetic view:

We view a power series as a function $f : \mathbb{C} \to \mathbb{C}$.

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What does $\sum_{n \geq 0} z^n = \frac{1}{1-z}$ mean in the algebraic view?

It means that the power series $1 - z$ and the power series $\sum_{n \geq 0} z^n$ are invers, i.e.,

$$(1 - z) \cdot \left( \sum_{n \geq 0} z^n \right) = 1.$$ 

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Hence, the generating function of the sequence \( a_n = n + 1 \)

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6.4 Generating Functions

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Hence, the generating function of the sequence 
\[ a_n = (n + 1)(n + 2) \] is \[ \frac{2}{(1-z)^3}. \]
Computing the $k$-th derivative of $\sum z^n$. 

Hence:

$\sum_{n \geq 0} \left( n + \frac{k}{k} \right) z^n = \frac{1}{(1-z)^{k+1}}$. 

The generating function of the sequence $a_n = \left( n + \frac{k}{k} \right)$ is $\frac{1}{(1-z)^{k+1}}$. 

6.4 Generating Functions
Computing the $k$-th derivative of $\sum z^n$.

\[ \sum_{n \geq k} n(n-1) \cdot \ldots \cdot (n-k+1) z^{n-k} \]
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Hence:

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6.4 Generating Functions

Ernst Mayr, Harald Räcke
6.4 Generating Functions

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\[ = \frac{z}{(1 - z)^2} \]
The generating function of the sequence $a_n = n$ is \( \frac{z}{(1-z)^2} \).
6.4 Generating Functions

We know

\[ \sum_{n \geq 0} y^n = \frac{1}{1 - y} \]

Hence,

\[ \sum_{n \geq 0} a^n z^n = \frac{1}{1 - az} \]

The generating function of the sequence \( f_n = a^n \) is \( \frac{1}{1-az} \).
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Example: $a_n = a_{n-1} + 1$, $a_0 = 1$

Suppose we have the recurrence $a_n = a_{n-1} + 1$ for $n \geq 1$ and $a_0 = 1$.

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Hence, \( a_n = n + 1 \).
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</tr>
<tr>
<td>$n + 1$</td>
<td>$\frac{1}{(1-z)^2}$</td>
</tr>
<tr>
<td>$(\binom{n+k}{k})$</td>
<td>$\frac{1}{(1-z)^{k+1}}$</td>
</tr>
<tr>
<td>$n$</td>
<td>$\frac{z}{(1-z)^2}$</td>
</tr>
<tr>
<td>$a^n$</td>
<td>$\frac{1}{1-az}$</td>
</tr>
<tr>
<td>$n^2$</td>
<td>$\frac{z(1+z)}{(1-z)^3}$</td>
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<th>\textit{n-th sequence element}</th>
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<td>1</td>
<td>( \frac{1}{1 - z} )</td>
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<td>$c f_n$</td>
<td>$c F$</td>
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- $n$-th sequence element
- generating function

$\sum_{n=0}^{\infty} f_n z^n = cF(z)$

$\sum_{n=k}^{\infty} f_n z^n = z^k F(z)$

$F(cz) = \sum_{n=0}^{\infty} f_n (cz)^n$
### Some Generating Functions

#### $n$-th sequence element

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<td>$n f_n$</td>
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Solving Recursions with Generating Functions

1. Set $A(z) = \sum_{n \geq 0} a_n z^n$. 

Techniques:
- partial fraction decomposition (Partialbruchzerlegung)
- lookup in tables
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1. Set \( A(z) = \sum_{n \geq 0} a_n z^n \).

2. Transform the right hand side so that boundary condition and recurrence relation can be plugged in.
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3. Do further transformations so that the infinite sums on the right hand side can be replaced by $A(z)$.

6. Write $f(z)$ as a formal power series. Techniques:
   - partial fraction decomposition (Partialbruchzerlegung)
   - lookup in tables

6.4 Generating Functions 11. Apr. 2018

Ernst Mayr, Harald Räcke
Solving Recursions with Generating Functions

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4. Solving for $A(z)$ gives an equation of the form $A(z) = f(z)$, where hopefully $f(z)$ is a simple function.
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   Techniques:
   - partial fraction decomposition (Partialbruchzerlegung)
   - lookup in tables
6. The coefficients of the resulting power series are the \( a_n \).
Example: \( a_n = 2a_{n-1}, \ a_0 = 1 \)

1. Set up generating function:
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Example: $a_n = 2a_{n-1}$, $a_0 = 1$

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2. Transform right hand side so that recurrence can be plugged in:

$$A(z) = a_0 + \sum_{n \geq 1} a_n z^n$$
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$$A(z) = a_0 + \sum_{n\geq 1} a_n z^n$$

2. Plug in:

$$A(z) = 1 + \sum_{n\geq 1} (2a_{n-1}) z^n$$
Example: \( a_n = 2a_{n-1}, \ a_0 = 1 \)
Example: $a_n = 2a_{n-1}, \ a_0 = 1$

3. Transform right hand side so that infinite sums can be replaced by $A(z)$ or by simple function.
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A(z) = 1 + \sum_{n \geq 1} (2a_{n-1})z^n
\]

\[
= 1 + 2z \sum_{n \geq 1} a_{n-1}z^{n-1}
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$$A(z) = \frac{1}{1 - 2z}$$
Example: $a_n = 2a_{n-1}, \ a_0 = 1$

5. Rewrite $f(z)$ as a power series:

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$$\sum_{n \geq 0} a_n z^n = A(z) = \frac{1}{1 - 2z} = \sum_{n \geq 0} 2^n z^n$$
Example: \( a_n = 3a_{n-1} + n, \ a_0 = 1 \)

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$$= 1 + 3z \sum_{n\geq 1} a_{n-1} z^{n-1} + \sum_{n\geq 1} n z^n$$
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= 1 + 3zA(z) + \frac{z}{(1 - z)^2}
\]
Example: \( a_n = 3a_{n-1} + n, \ a_0 = 1 \)

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A(z) = 1 + 3zA(z) + \frac{z}{(1 - z)^2}
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gives

\[
A(z) = \frac{(1 - z)^2 + z}{(1 - 3z)(1 - z)^2}
\]
Example: $a_n = 3a_{n-1} + n, \ a_0 = 1$

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$$A(z) = 1 + 3zA(z) + \frac{z}{(1 - z)^2}$$

gives

$$A(z) = \frac{(1 - z)^2 + z}{(1 - 3z)(1 - z)^2} = \frac{z^2 - z + 1}{(1 - 3z)(1 - z)^2}$$
Example: \( a_n = 3a_{n-1} + n, \ a_0 = 1 \)

5. Write \( f(z) \) as a formal power series:

We use partial fraction decomposition:
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We use partial fraction decomposition:

\[
\frac{z^2 - z + 1}{(1 - 3z)(1 - z)^2} = \frac{A}{1 - 3z} + \frac{B}{1 - z} + \frac{C}{(1 - z)^2}
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Example: $a_n = 3a_{n-1} + n, \ a_0 = 1$

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This gives

$$z^2 - z + 1 = A(1 - z)^2 + B(1 - 3z)(1 - z) + C(1 - 3z)$$
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We use partial fraction decomposition:

$$\frac{z^2 - z + 1}{(1 - 3z)(1 - z)^2} \equiv \frac{A}{1 - 3z} + \frac{B}{1 - z} + \frac{C}{(1 - z)^2}$$

This gives

$$z^2 - z + 1 = A(1 - z)^2 + B(1 - 3z)(1 - z) + C(1 - 3z)$$

$$= A(1 - 2z + z^2) + B(1 - 4z + 3z^2) + C(1 - 3z)$$
**Example:** \( a_n = 3a_{n-1} + n, \ a_0 = 1 \)

5. Write \( f(z) \) as a formal power series:

We use partial fraction decomposition:

\[
\frac{z^2 - z + 1}{(1 - 3z)(1 - z)^2} = \frac{A}{1 - 3z} + \frac{B}{1 - z} + \frac{C}{(1 - z)^2}
\]

This gives

\[
z^2 - z + 1 = A(1 - z)^2 + B(1 - 3z)(1 - z) + C(1 - 3z)
\]

\[
= A(1 - 2z + z^2) + B(1 - 4z + 3z^2) + C(1 - 3z)
\]

\[
= (A + 3B)z^2 + (-2A - 4B - 3C)z + (A + B + C)
\]
Example: \( a_n = 3a_{n-1} + n, \ a_0 = 1 \)

5. Write \( f(z) \) as a formal power series:

This leads to the following conditions:

\[
A + B + C = 1
\]
\[
2A + 4B + 3C = 1
\]
\[
A + 3B = 1
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Example: $a_n = 3a_{n-1} + n, \ a_0 = 1$

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This leads to the following conditions:

\[
A + B + C = 1 \\
2A + 4B + 3C = 1 \\
A + 3B = 1
\]

which gives

\[
A = \frac{7}{4} \quad B = -\frac{1}{4} \quad C = -\frac{1}{2}
\]
Example: \(a_n = 3a_{n-1} + n, \ a_0 = 1\)

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5. Write \( f(z) \) as a formal power series:

\[
A(z) = \frac{7}{4} \cdot \frac{1}{1 - 3z} - \frac{1}{4} \cdot \frac{1}{1 - z} - \frac{1}{2} \cdot \frac{1}{(1 - z)^2}
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Example: $a_n = 3a_{n-1} + n, \ a_0 = 1$

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$$= \frac{7}{4} \cdot \sum_{n \geq 0} 3^n z^n - \frac{1}{4} \cdot \sum_{n \geq 0} z^n - \frac{1}{2} \cdot \sum_{n \geq 0} (n + 1) z^n$$
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5. Write \( f(z) \) as a formal power series:

\[
A(z) = \frac{7}{4} \cdot \frac{1}{1 - 3z} - \frac{1}{4} \cdot \frac{1}{1 - z} - \frac{1}{2} \cdot \frac{1}{(1 - z)^2}
\]

\[
= \frac{7}{4} \cdot \sum_{n \geq 0} 3^n z^n - \frac{1}{4} \cdot \sum_{n \geq 0} z^n - \frac{1}{2} \cdot \sum_{n \geq 0} (n + 1) z^n
\]

\[
= \sum_{n \geq 0} \left( \frac{7}{4} \cdot 3^n - \frac{1}{4} - \frac{1}{2} (n + 1) \right) z^n
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Example: \( a_n = 3a_{n-1} + n, \; a_0 = 1 \)

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\[= \sum_{n \geq 0} \left( \frac{7}{4} \cdot 3^n - \frac{1}{2} n - \frac{3}{4} \right) z^n
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Example: $a_n = 3a_{n-1} + n, \ a_0 = 1$

5. Write $f(z)$ as a formal power series:

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6. This means $a_n = \frac{7}{4} 3^n - \frac{1}{2} n - \frac{3}{4}$. 

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6.4 Generating Functions
6.5 Transformation of the Recurrence

Example 9

\[ f_0 = 1 \]
\[ f_1 = 2 \]
\[ f_n = f_{n-1} \cdot f_{n-2} \text{ for } n \geq 2. \]
6.5 Transformation of the Recurrence

Example 9

\[ f_0 = 1 \]
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\[ f_n = f_{n-1} \cdot f_{n-2} \text{ for } n \geq 2. \]

Define

\[ g_n := \log f_n. \]
Example 9

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Define

\[ g_n := \log f_n. \]

Then

\[ g_n = g_{n-1} + g_{n-2} \text{ for } n \geq 2. \]
Example 9

\[
\begin{align*}
    f_0 & = 1 \\
    f_1 & = 2 \\
    f_n & = f_{n-1} \cdot f_{n-2} \text{ for } n \geq 2.
\end{align*}
\]

Define

\[ g_n := \log f_n. \]

Then

\[
\begin{align*}
    g_n & = g_{n-1} + g_{n-2} \text{ for } n \geq 2 \\
    g_1 & = \log 2 = 1 (\text{for } \log = \log_2), \quad g_0 = 0
\end{align*}
\]
Example 9

\[ f_0 = 1 \]
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\[ g_n = g_{n-1} + g_{n-2} \text{ for } n \geq 2 \]
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\[ g_n = F_n \text{ (} n \text{-th Fibonacci number)} \]
6.5 Transformation of the Recurrence

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\[ g_1 = \log 2 = 1 (\text{for } \log = \log_2), \quad g_0 = 0 \]
\[ g_n = F_n \text{ (n-th Fibonacci number)} \]
\[ f_n = 2^{F_n} \]
6.5 Transformation of the Recurrence

Example 10

\[ f_1 = 1 \]
\[ f_n = 3f_{\frac{n}{2}} + n; \text{ for } n = 2^k, \ k \geq 1; \]
Example 10

\[ f_1 = 1 \]
\[ f_n = 3 f_{\frac{n}{2}} + n; \text{ for } n = 2^k, \ k \geq 1 ; \]

Define

\[ g_k := f_{2k} . \]
6.5 Transformation of the Recurrence

Example 10

\[ f_1 = 1 \]
\[ f_n = 3f_{n/2} + n; \text{ for } n = 2^k, k \geq 1; \]

Define

\[ g_k := f_{2^k}. \]

Then:

\[ g_0 = 1 \]
6.5 Transformation of the Recurrence

Example 10

\[ f_1 = 1 \]
\[ f_n = 3f_{\frac{n}{2}} + n; \text{ for } n = 2^k, \; k \geq 1 \; ; \]

Define

\[ g_k := f_{2^k} . \]

Then:

\[ g_0 = 1 \]
\[ g_k = 3g_{k-1} + 2^k, \; k \geq 1 \]
6 Recurrences

We get

\[ g_k = 3\left[g_{k-1}\right] + 2^k \]
6 Recurrences

We get

\[ g_k = 3 \left[ g_{k-1} \right] + 2^k \]
\[ = 3 \left[ 3g_{k-2} + 2^{k-1} \right] + 2^k \]
6 Recurrences

We get

\[ g_k = 3 \left[ g_{k-1} \right] + 2^k \]
\[ = 3 \left[ 3g_{k-2} + 2^{k-1} \right] + 2^k \]
\[ = 3^2 \left[ g_{k-2} \right] + 32^{k-1} + 2^k \]
6 Recurrences

We get

\[ g_k = 3 \left[ g_{k-1} \right] + 2^k \]
\[ = 3 \left[ 3g_{k-2} + 2^{k-1} \right] + 2^k \]
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\[ = 3^2 \left[ 3g_{k-3} + 2^{k-2} \right] + 32^{k-1} + 2^k \]
6 Recurrences

We get

\[ g_k = 3 \left[ g_{k-1} \right] + 2^k \]
\[ = 3 \left[ 3g_{k-2} + 2^{k-1} \right] + 2^k \]
\[ = 3^2 \left[ g_{k-2} \right] + 32^{k-1} + 2^k \]
\[ = 3^2 \left[ 3g_{k-3} + 2^{k-2} \right] + 32^{k-1} + 2^k \]
\[ = 3^3 g_{k-3} + 3^2 2^{k-2} + 32^{k-1} + 2^k \]
6 Recurrences

We get

\[ g_k = 3 [g_{k-1}] + 2^k \]

\[ = 3 \left[ 3g_{k-2} + 2^{k-1} \right] + 2^k \]

\[ = 3^2 \left[ g_{k-2} \right] + 32^{k-1} + 2^k \]

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\[ = 3^3 g_{k-3} + 3^2 2^{k-2} + 32^{k-1} + 2^k \]

\[ = 2^k \cdot \sum_{i=0}^{k} \left( \frac{3}{2} \right)^i \]
We get

\[ g_k = 3 \left[ g_{k-1} \right] + 2^k \]

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\[ = 3^2 \left[ g_{k-2} \right] + 32^{k-1} + 2^k \]

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\[ = 3^3 g_{k-3} + 3^2 2^{k-2} + 32^{k-1} + 2^k \]

\[ = 2^k \cdot \sum_{i=0}^{k} \left( \frac{3}{2} \right)^i \]

\[ = 2^k \cdot \frac{(\frac{3}{2})^{k+1} - 1}{1/2} \]
6 Recurrences

We get

\[ g_k = 3 \left[ g_{k-1} \right] + 2^k \]

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\[ = 3^2 \left[ g_{k-2} \right] + 32^{k-1} + 2^k \]

\[ = 3^2 \left[ 3g_{k-3} + 2^{k-2} \right] + 32^{k-1} + 2^k \]

\[ = 3^3 g_{k-3} + 3^2 2^{k-2} + 32^{k-1} + 2^k \]

\[ = 2^k \cdot \sum_{i=0}^{k} \left( \frac{3}{2} \right)^i \]

\[ = 2^k \cdot \frac{\left( \frac{3}{2} \right)^{k+1} - 1}{1/2} = 3^{k+1} - 2^{k+1} \]
Let $n = 2^k$:

$$g_k = 3^{k+1} - 2^{k+1}, \text{ hence }$$

$$f_n = 3 \cdot 3^k - 2 \cdot 2^k$$
Let $n = 2^k$:

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6 Recurrences

Let $n = 2^k$:

$$g_k = 3^{k+1} - 2^{k+1}, \text{ hence}$$

$$f_n = 3 \cdot 3^k - 2 \cdot 2^k$$

$$= 3 (2 \log 3)^k - 2 \cdot 2^k$$

$$= 3 (2^k)^{\log 3} - 2 \cdot 2^k$$
Let $n = 2^k$:

\[
\begin{align*}
\mathcal{g}_k &= 3^{k+1} - 2^{k+1}, \text{ hence} \\
\mathcal{f}_n &= 3 \cdot 3^k - 2 \cdot 2^k \\
&= 3(2^{\log_3})^k - 2 \cdot 2^k \\
&= 3(2^k)^{\log_3} - 2 \cdot 2^k \\
&= 3n^{\log_3} - 2n .
\end{align*}
\]