

Algorithms: COMP3121/3821/9101/9801

Aleks Ignjatović

School of Computer Science and Engineering University of New South Wales

TOPIC 2: FAST LARGE INTEGER MULTIPLICATION



Basics revisited: how do we multiply two numbers?

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• The primary school algorithm:

• Can we do it faster than in n^2 many steps??

$$A = A_1 2^{\frac{n}{2}} + A_0 \qquad A = \underbrace{XX \dots X}_{n/2 \ bits} \underbrace{XX \dots X}_{n/2 \ bits}$$

$$B = B_1 2^{\frac{n}{2}} + B_0$$

• Take the two input numbers A and B, and split them into two halves:

$$A = A_1 2^{\frac{n}{2}} + A_0 \qquad A = \underbrace{XX \dots X}_{n/2 \ bits} \underbrace{XX \dots X}_{n/2 \ bits}$$

$$B = B_1 2^{\frac{n}{2}} + B_0$$

• $A_1 = \text{MoreSignificantPart}(A); \quad A_0 = \text{LessSignificantPart}(A);$

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= $A_1 B_1 2^n + ((A_1 + A_0)(B_1 + B_0) - A_1 B_1 - A_0 B_0) 2^{\frac{n}{2}} + A_0 B_0$

```
1: function MULT(A, B)
        if |A| = |B| = 1 then return AB
 2:
        else
 3:
 4:
             A_1 \leftarrow \text{MoreSignificantPart}(A);
             A_0 \leftarrow \text{LessSignificantPart}(A);
 5:
             B_1 \leftarrow \text{MoreSignificantPart}(B);
 6:
        B_0 \leftarrow \text{LessSignificantPart}(B);
 7:
        U \leftarrow A_0 + A_1:
 8:
        V \leftarrow B_0 + B_1:
 9:
    X \leftarrow \text{MULT}(A_0, B_0);
10:
             W \leftarrow \text{MULT}(A_1, B_1):
11:
             Y \leftarrow \text{Mult}(U, V):
12:
             return W 2^n + (Y - X - W) 2^{n/2} + X
13:
14:
        end if
```

15: end function

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- Thus, the first case of the Master Theorem applies.
- Consequently,

$$T(n) = \Theta(n^{\log_2 3}) < \Theta(n^{1.585})$$

without going through the messy calculations!



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• So,

$$AB = A_2 B_2 2^{4k} + (A_2 B_1 + A_1 B_2) 2^{3k} + (A_2 B_0 + A_1 B_1 + A_0 B_2) 2^{2k} + (A_1 B_0 + A_0 B_1) 2^k + A_0 B_0$$

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$$(A_2 + A_1 + A_0)(B_2 + B_1 + B_0) = A_0B_0 + A_1B_0 + A_2B_0 + A_0B_1 + A_1B_1 + A_2B_1 + A_0B_2 + A_1B_2 + A_2B_2 ???$$



$$AB = A_2 B_2 2^{4k} + (A_2 B_1 + A_1 B_2) 2^{3k} + (A_2 B_0 + A_1 B_1 + A_0 B_2) 2^{2k} + (A_1 B_0 + A_0 B_1) 2^k + A_0 B_0$$

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• Not clear at all how to get $C_0 - C_4$ with 5 multiplications only ...

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$$P_A(x) = A_2 x^2 + A_1 x + A_0;$$

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Note that

$$A = A_2 (2^k)^2 + A_1 2^k + A_0 = P_A(2^k);$$

$$B = B_2 (2^k)^2 + B_1 2^k + B_0 = P_B(2^k).$$



• If we manage to compute somehow the product polynomial 多项式

$$P_C(x) = P_A(x)P_B(x) = C_4 x^4 + C_3 x^3 + C_2 x^2 + C_1 x + C_0,$$

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with only 5 multiplications, we can then obtain the product of numbers A and B simply as

$$A \cdot B = P_A(2^k)P_B(2^k) = P_C(2^k) = C_4 2^{4k} + C_3 2^{3k} + C_2 2^{2k} + C_1 2^k + C_0,$$

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- We choose the smallest possible 5 integer values (smallest by their absolute value), i.e., -2, -1, 0, 1, 2.

• Thus, we compute
$$P_A(-2)$$
, $P_A(-1)$, $P_A(0)$, $P_A(1)$, $P_A(2)$
 $P_B(-2)$, $P_B(-1)$, $P_B(0)$, $P_B(1)$, $P_B(2)$

• For $P_A(x) = A_2 x^2 + A_1 x + A_0$ we have

$$P_A(-2) = A_2(-2)^2 + A_1(-2) + A_0 = 4A_2 - 2A_1 + A_0$$

$$P_A(-1) = A_2(-1)^2 + A_1(-1) + A_0 = A_2 - A_1 + A_0$$

$$P_A(0) = A_20^2 + A_10 + A_0 = A_0$$

$$P_A(1) = A_21^2 + A_11 + A_0 = A_2 + A_1 + A_0$$

$$P_A(2) = A_22^2 + A_12 + A_0 = 4A_2 + 2A_1 + A_0.$$

• For $P_A(x) = A_2 x^2 + A_1 x + A_0$ we have $P_A(-2) = A_2 (-2)^2 + A_1 (-2) + A_0 = 4A_2 - 2A_1 + A_0$ $P_A(-1) = A_2 (-1)^2 + A_1 (-1) + A_0 = A_2 - A_1 + A_0$ $P_A(0) = A_2 0^2 + A_1 0 + A_0 = A_0$ $P_A(1) = A_2 1^2 + A_1 1 + A_0 = A_2 + A_1 + A_0$ $P_A(2) = A_2 2^2 + A_1 2 + A_0 = 4A_2 + 2A_1 + A_0$

• Similarly, for
$$P_B(x) = B_2 x^2 + B_1 x + B_0$$
 we have
$$P_B(-2) = B_2 (-2)^2 + B_1 (-2) + B_0 = 4B_2 - 2B_1 + B_0$$

$$P_B(-1) = B_2 (-1)^2 + B_1 (-1) + B_0 = B_2 - B_1 + B_0$$

$$P_B(0) = B_2 0^2 + B_1 0 + B_0 = B_0$$

$$P_B(1) = B_2 1^2 + B_1 1 + B_0 = B_2 + B_1 + B_0$$

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• Similarly, for $P_B(x) = B_2 x^2 + B_1 x + B_0$ we have

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• These evaluations involve only additions because 2A = A + A; 4A = 2A + 2A.

• Having obtained $P_A(-2)$, $P_A(-1)$, $P_A(0)$, $P_A(1)$, $P_A(2)$ and $P_B(-2)$, $P_B(-1)$, $P_B(0)$, $P_B(1)$, $P_B(2)$ we can now obtain $P_C(-2)$, $P_C(-1)$, $P_C(0)$, $P_C(1)$, $P_C(2)$ with only 5 multiplications of large numbers:

$$P_{C}(-2) = P_{A}(-2)P_{B}(-2)$$

$$= (A_{0} - 2A_{1} + 4A_{2})(B_{0} - 2B_{1} + 4B_{2})$$

$$P_{C}(-1) = P_{A}(-1)P_{B}(-1)$$

$$= (A_{0} - A_{1} + A_{2})(B_{0} - B_{1} + B_{2})$$

$$P_{C}(0) = P_{A}(0)P_{B}(0)$$

$$= A_{0}B_{0}$$

$$P_{C}(1) = P_{A}(1)P_{B}(1)$$

$$= (A_{0} + A_{1} + A_{2})(B_{0} + B_{1} + B_{2})$$

$$P_{C}(2) = P_{A}(2)P_{B}(2)$$

$$= (A_{0} + 2A_{1} + 4A_{2})(B_{0} + 2B_{1} + 4B_{2})$$

• Thus, if we represent the product $C(x) = P_A(x)P_B(x)$ in the coefficient form as $C(x) = C_4x^4 + C_3x^3 + C_2x^2 + C_1x + C_0$ we get

$$C_4(-2)^4 + C_3(-2)^3 + C_2(-2)^2 + C_1(-2) + C_0 = P_C(-2) = P_A(-2)P_B(-2)$$

$$C_4(-1)^4 + C_3(-1)^3 + C_2(-1)^2 + C_1(-1) + C_0 = P_C(-1) = P_A(-1)P_B(-1)$$

$$C_40^4 + C_30^3 + C_20^2 + C_1 \cdot 0 + C_0 = P_C(0) = P_A(0)P_B(0)$$

$$C_41^4 + C_31^3 + C_21^2 + C_1 \cdot 1 + C_0 = P_C(1) = P_A(1)P_B(1)$$

$$C_42^4 + C_32^3 + C_22^2 + C_1 \cdot 2 + C_0 = P_C(2) = P_A(2)P_B(2).$$

• Thus, if we represent the product $C(x) = P_A(x)P_B(x)$ in the coefficient form as $C(x) = C_4x^4 + C_3x^3 + C_2x^2 + C_1x + C_0$ we get

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Simplifying the left side we obtain

$$16C_4 - 8C_3 + 4C_2 - 2C_1 + C_0 = P_C(-2)$$

$$C_4 - C_3 + C_2 - C_1 + C_0 = P_C(-1)$$

$$C_0 = P_C(0)$$

$$C_4 + C_3 + C_2 + C_1 + C_0 = P_C(1)$$

$$16C_4 + 8C_3 + 4C_2 + 2C_1 + C_0 = P_C(2)$$

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$$C_{0} = P_{C}(0)$$

$$C_{1} = \frac{P_{C}(-2)}{12} - \frac{2P_{C}(-1)}{3} + \frac{2P_{C}(1)}{3} - \frac{P_{C}(2)}{12}$$

$$C_{2} = -\frac{P_{C}(-2)}{24} + \frac{2P_{C}(-1)}{3} - \frac{5P_{C}(0)}{4} + \frac{2P_{C}(1)}{3} - \frac{P_{C}(2)}{24}$$

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• Here is the complete algorithm:

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1: function MULT(A, B)

2: obtain A_0, A_1, A_2 and B_0, B_1, B_2 such that $A = A_2 2^{2k} + A_1 2^k + A_0$; $B = B_2 2^{2k} + B_1 2^k + B_0$;

3: form polynomials $P_A(x) = A_2 x^2 + A_1 x + A_0$; $P_B(x) = B_2 x^2 + B_1 x + B_0$;

4:
$$P_{A}(-2) \leftarrow 4A_{2} - 2A_{1} + A_{0} \qquad P_{B}(-2) \leftarrow 4B_{2} - 2B_{1} + B_{0}$$

$$P_{A}(-1) \leftarrow A_{2} - A_{1} + A_{0} \qquad P_{B}(-1) \leftarrow B_{2} - B_{1} + B_{0}$$

$$P_{A}(0) \leftarrow A_{0} \qquad P_{B}(0) \leftarrow B_{0}$$

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5:
$$P_{A}(2) \leftarrow A_{A}(2) \leftarrow A_{A}(2) = A_{$$

$$P_{C}(-2) \leftarrow \text{MULT}(P_{A}(-2), P_{B}(-2)); \qquad P_{C}(-1) \leftarrow \text{MULT}(P_{A}(-1), P_{B}(-1));$$

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7: form
$$P_C(x) = C_4 x^4 + C_3 x^3 + C_2 x^2 + C_1 x + C_0$$
; compute $P_C(2^k) = C_4 2^{4k} + C_2 2^{3k} + C_2 2^{2k} + C_1 2^k + C_0$

8: return $P_C(2^k) = A \cdot B$.

9: end function

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分成3份5个多项式

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- Clearly, the first case of the MT applies and we get $T(n) = O(n^{\log_3 5}) < O(n^{1.47})$.

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- The answer is, in a sense, BOTH yes and no, so lets see what happens if we slice numbers into n+1 many equal slices...

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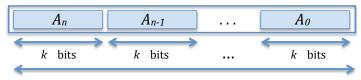
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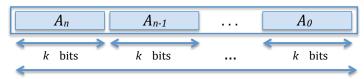
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• Example:

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we have

$$P_A(x) \cdot P_B(x) = \sum_{j=0}^{2n} \left(\sum_{i+k=j} A_i B_k \right) x^j = \sum_{j=0}^{2n} C_j x^j$$

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• We need to find the coefficients $C_j = \sum_{i+k=j} A_i B_k$ without performing $(n+1)^2$ many multiplications necessary to get all products of the form $A_i B_k$.

A VERY IMPORTANT DIGRESSION:

If you have two sequences $\vec{A} = (A_0, A_1, \dots, A_{n-1}, A_n)$ and $\vec{B} = (B_0, B_1, \dots, B_{m-1}, B_m)$, and if you form the two corresponding polynomials

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then the sequence $\vec{C} = (C_0, C_1, \dots, C_{n+m})$ of the coefficients of the product polynomial, with these coefficients given by

$$C_j = \sum_{i+k=j} A_i B_k$$
, for $0 \le j \le n+m$,

is **extremely important** and is called the **LINEAR CONVOLUTION** of sequences \vec{A} and \vec{B} and is denoted by $\vec{C} = \vec{A} \star \vec{B}$.



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- In signal processing these degrees can be greater than 1000.
- This is the main reason for us to study methods of fast computation of convolutions (aside of finding products of large integers, which is what we are doing at the moment).

• Every polynomial $P_A(x)$ of degree n is uniquely determined by its values at any n+1 distinct input values x_0, x_1, \ldots, x_n :

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• For $P_A(x) = A_n x^n + A_{n-1} x^{n-1} + \ldots + A_0$, these values can be obtained via a matrix multiplication:

$$\begin{pmatrix} 1 & x_0 & x_0^2 & \dots & x_0^n \\ 1 & x_1 & x_1^2 & \dots & x_1^n \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & x_n & x_n^2 & \dots & x_n^n \end{pmatrix} \begin{pmatrix} A_0 \\ A_1 \\ \vdots \\ A_n \end{pmatrix} = \begin{pmatrix} P_A(x_0) \\ P_A(x_1) \\ \vdots \\ P_A(x_n) \end{pmatrix}. \tag{1}$$

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- Such a matrix is called the Vandermonde matrix.



• Thus, if all x_i are all distinct, given any values $P_A(x_0), P_A(x_1), \ldots, P_A(x_n)$ the coefficients A_0, A_1, \ldots, A_n of the polynomial $P_A(x)$ are uniquely determined:

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 - **1** a representation of a polynomial $P_A(x)$ via its coefficients $A_n, A_{n-1}, \ldots, A_0$, i.e. $P_A(x) = A_n x^n + \ldots + A_1 x + A_0$

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 - 2 a representation of a polynomial $P_A(x)$ via its values

$$P_A(x) \leftrightarrow \{(x_0, P_A(x_0)), (x_1, P_A(x_1)), \dots, (x_n, P_A(x_n))\}$$



• If we fix the inputs x_0, x_1, \ldots, x_n then commuting between a representation of a polynomial $P_A(x)$ via its coefficients and a representation via its values at these points is done via the following two matrix multiplications, with matrices made up from **constants**:

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• Thus, for fixed input values x_0, \ldots, x_n this switch between the two kinds of representations is done in **linear time**!

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$$P_{A}(x)P_{B}(x) \leftrightarrow \{(x_{0}, \underbrace{P_{A}(x_{0})P_{B}(x_{0})}_{P_{C}(x_{0})}), (x_{1}, \underbrace{P_{A}(x_{1})P_{B}(x_{1})}_{P_{C}(x_{1})}), \dots, (x_{2n}, \underbrace{P_{A}(x_{2n})P_{B}(x_{2n})}_{P_{C}(x_{2n})})\}$$

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3 Convert such value representation of $P_C(x) = P_A(x)P_B(x)$ back to coefficient form

$$P_C(x) = C_{2n}x^{2n} + C_{2n-1}x^{2n-1} + \dots + C_1x + C_0;$$

Fast multiplication of polynomials - continued

• What values should we choose for x_0, x_1, \ldots, x_{2n} ??

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• So we find the values $P_A(m)$ and $P_B(m)$ for all m such that $-n \leq m \leq n$.

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- Multiplication of a large number with k bits by a constant integer d can be done in time linear in k because it is reducible to d-1 additions:

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$$P_A(m) = A_n m^n + A_{n-1} m^{n-1} + \dots + A_0 : -n \le m \le n,$$

$$P_B(m) = B_n m^n + B_{n-1} m^{n-1} + \dots + B_0: \quad -n \le m \le n.$$

can be found in time linear in the number of bits of the input numbers!



• We now perform 2n + 1 multiplications of large numbers to obtain

$$P_A(-n)P_B(-n), \ldots, P_A(-1)P_B(-1), P_A(0)P_B(0), P_A(1)P_B(1), \ldots, P_A(n)P_B(n)$$

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• For $P_C(x) = P_A(x)P_B(x)$ these products are 2n + 1 many values of $P_C(x)$:

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• For $P_C(x) = P_A(x)P_B(x)$ these products are 2n + 1 many values of $P_C(x)$:

$$P_C(-n) = P_A(-n)P_B(-n), \dots, P_C(0) = P_A(0)P_B(0), \dots, P_C(n) = P_A(n)P_B(n)$$

• Let C_0, C_1, \ldots, C_{2n} be the coefficients of the product polynomial C(x), i.e., let

$$P_C(x) = C_{2n}x^{2n} + C_{2n-1}x^{2n-1} + \dots + C_0,$$

• We now have:

$$C_{2n}(-n)^{2n} + C_{2n-1}(-n)^{2n-1} + \dots + C_0 = P_C(-n)$$

$$C_{2n}(-(n-1))^{2n} + C_{2n-1}(-(n-1))^{2n-1} + \dots + C_0 = P_C(-(n-1))$$

$$\vdots$$

$$C_{2n}(n-1)^{2n} + C_{2n-1}(n-1)^{2n-1} + \dots + C_0 = P_C(n-1)$$

$$C_{2n}n^{2n} + C_{2n-1}n^{2n-1} + \dots + C_0 = P_C(n)$$

• This is just a system of linear equations, that can be solved for C_0, C_1, \ldots, C_{2n} :

$$\begin{pmatrix} 1 & -n & (-n)^2 & \dots & (-n)^{2n} \\ 1 & -(n-1) & (-(n-1))^2 & \dots & (-(n-1))^{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 1 & n & n^2 & \dots & n^{2n} \end{pmatrix} \begin{pmatrix} C_0 \\ C_1 \\ \vdots \\ C_{2n} \end{pmatrix} = \begin{pmatrix} P_C(-n) \\ P_C(-(n-1)) \\ \vdots \\ P_C(n) \end{pmatrix},$$

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- Thus the coefficients C_i can be obtained in linear time.
- So here is the algorithm we have just described:



1: function MULT(n, A, B)

2: if |A| = |B| = 1 then return AB

3: else

4: obtain n+1 slices A_0, A_1, \ldots, A_n and B_0, B_1, \ldots, B_n such that

$$A = A_n 2^{n k} + A_{n-1} 2^{(n-1) k} + \dots + A_0$$
$$B = B_n 2^{n k} + B_{n-1} 2^{(n-1) k} + \dots + B_0$$

5: form polynomials

$$P_A(x) = A_n x^n + A_{n-1} x^{(n-1)} + \dots + A_0$$

$$P_B(x) = B_n x^n + B_{n-1} x^{(n-1)} + \dots + B_0$$

6: for m = -n to m = n do

7: compute $P_A(m)$ and $P_B(m)$;

8: $P_C(m) \leftarrow \text{MULT}(n, P_A(m)P_B(m))$

9: end for

10: compute $C_0, C_1, \ldots C_{2n}$ via

$$\begin{pmatrix} C_0 \\ C_1 \\ \vdots \\ C_{2n} \end{pmatrix} = \begin{pmatrix} 1 & -n & (-n)^2 & \dots & (-n)^{2n} \\ 1 & -(n-1) & (-(n-1))^2 & \dots & (-(n-1))^{2n} \\ \vdots & \vdots & & \vdots & & \vdots \\ 1 & n & n^2 & \dots & n^{2n} \end{pmatrix}^{-1} \begin{pmatrix} P_C(-n) \\ P_C(-(n-1)) \\ \vdots \\ P_C(n) \end{pmatrix}.$$

11: form $P_C(x) = C_{2n}x^{2n} + ... + C_0$ and compute $P_C(2^k)$

12: return $P_C(2^k) = A \cdot B$

13: end if

14: end function

ullet it is easy to see that the values of the two polynomials we are multiplying have at most k+s bits where s is a constant which depends on n but does NOT depend on k:

$$P_A(m) = A_n m^n + A_{n-1} m^{n-1} + \dots + A_0 : -n \le m \le n.$$

This is because each A_i is smaller than 2^k because each A_k has k bits; thus

$$|P_A(m)| < n^n(|A_n| + |A_{n-1}| + \dots + |A_0|) < n^n \times n \times 2^k$$

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• Since s is constant, its impact can be neglected.



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- Thus, with a = 2n + 1 and b = n + 1 the first case of the Master Theorem applies;
- so we get:

$$T(N) = \Theta\left(N^{\log_b a}\right) = \Theta\left(N^{\log_{n+1}(2n+1)}\right)$$

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• Thus, we would have to slice the input numbers into $2^{10} = 1024$ pieces!!

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- Consequently, slicing the input numbers in more than just a few slices results in a hopelessly slow algorithm, despite the fact that the asymptotic bounds improve as we increase the number of slices!
- The moral is: In practice, asymptotic estimates are useless if the size of the constants hidden by the *O*-notation are not estimated and found to be reasonably small!!!

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- After we study the FFT we will have a guest lecture by a Dolby engineer to demonstrate to you some cool applications of FFT.