

29 marzo 2023

Moltiplicazioni di Matrici

Relazioni di ricorrenza

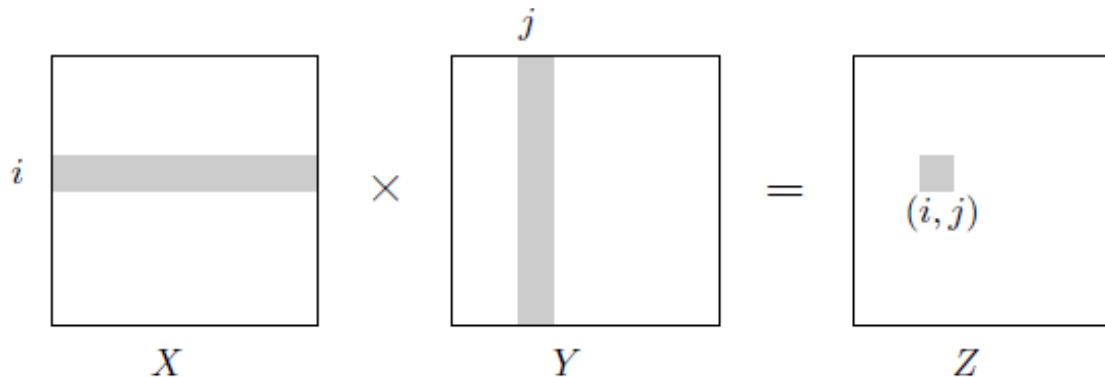
Teoremi generali

# Matrix Multiplication (and decimal wars!)

Ref. [KT] no; [DPV, CLRS] si

# Matrix Multiplication

**Matrix multiplication.** Given two  $n$ -by- $n$  matrices  $X$  and  $Y$ , compute  $X Y = Z$ .



**Brute force.**  $\Theta(n^3)$  arithmetic operations.

**Fundamental question.** Can we improve upon brute force?

# Matrix Multiplication: Warmup

Divide-and-conquer.

**Divide:** partition A and B into  $\frac{1}{2}n$ -by- $\frac{1}{2}n$  blocks.

**Conquer:** multiply 8  $\frac{1}{2}n$ -by- $\frac{1}{2}n$  recursively.

**Combine:** add appropriate products using 4 matrix additions.

$$\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \times \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}$$

$$\begin{aligned} C_{11} &= (A_{11} \times B_{11}) + (A_{12} \times B_{21}) \\ C_{12} &= (A_{11} \times B_{12}) + (A_{12} \times B_{22}) \\ C_{21} &= (A_{21} \times B_{11}) + (A_{22} \times B_{21}) \\ C_{22} &= (A_{21} \times B_{12}) + (A_{22} \times B_{22}) \end{aligned}$$

$$T(n) = \underbrace{8T(n/2)}_{\text{recursive calls}} + \underbrace{\Theta(n^2)}_{\text{add, form submatrices}} \Rightarrow T(n) = \Theta(n^3)$$

# Matrix Multiplication: Key Idea

**Key idea.** multiply 2-by-2 block matrices with only 7 multiplications.

$$\begin{bmatrix} C_{11} & C_{12} \\ C_{21} & C_{22} \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \times \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}$$

$$C_{11} = P_5 + P_4 - P_2 + P_6$$

$$C_{12} = P_1 + P_2$$

$$C_{21} = P_3 + P_4$$

$$C_{22} = P_5 + P_1 - P_3 - P_7$$

$$P_1 = A_{11} \times (B_{12} - B_{22})$$

$$P_2 = (A_{11} + A_{12}) \times B_{22}$$

$$P_3 = (A_{21} + A_{22}) \times B_{11}$$

$$P_4 = A_{22} \times (B_{21} - B_{11})$$

$$P_5 = (A_{11} + A_{22}) \times (B_{11} + B_{22})$$

$$P_6 = (A_{12} - A_{22}) \times (B_{21} + B_{22})$$

$$P_7 = (A_{11} - A_{21}) \times (B_{11} + B_{12})$$

# Fast Matrix Multiplication

## Fast matrix multiplication. (Strassen, 1969)

**Divide:** partition A and B into  $\frac{1}{2}n$ -by- $\frac{1}{2}n$  blocks.

Compute: 14  $\frac{1}{2}n$ -by- $\frac{1}{2}n$  matrices via 10 matrix additions.

**Conquer:** multiply 7  $\frac{1}{2}n$ -by- $\frac{1}{2}n$  matrices recursively.

**Combine:** 7 products into 4 terms using 8 matrix additions.

## Analysis.

Assume  $n$  is a power of 2.

$T(n)$  = # arithmetic operations.

$$T(n) = \underbrace{7T(n/2)}_{\text{recursive calls}} + \underbrace{\Theta(n^2)}_{\text{add, subtract}} \Rightarrow T(n) = \Theta(n^{\log_2 7}) = O(n^{2.81})$$

The next **big improvement** took place in the **late 1970s**,

**New approach**, (Arnold Schönhage):

It involves translating/reducing **matrix multiplication** into a different computational problem in linear algebra involving objects called **tensors**.

The particular tensors used in this problem are three-dimensional arrays of numbers composed of many different parts, each of which looks like a small matrix multiplication problem.

Strassen later called this approach the “**laser method**.”

Matrix multiplication and this problem involving tensors are equivalent to each other in a sense, yet researchers already had **faster procedures for solving the latter one**.

This is a very common paradigm in theoretical computer science: **reducing** between problems

# Decimal war!

1969	$O(n^{2.81})$	[Strassen]
1979 (December):	$O(n^{2.521813})$	
1980 (January):	$O(n^{2.521801})$	[Schönhage (laser method- tensor 3D)]
1987:	$O(n^{2.376})$	[Coppersmith-Winograd]
2012:	$O(n^{2.372873})$	[V. Vassilevska Williams]
2014:	$O(n^{2.3728639})$	[François Le Gall]
2020:	$O(n^{2.3728596})$	[V. Vassilevska Williams, J. Alman]
2022 (October):	$O(n^{2.37188})$	???
		[Duan, Wu and Zhou]
		[announced in a preprint]



# Fast Matrix Multiplication in Theory

Best known:  $O(n^{2.3728596})$  [2020]



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Harvard University

# Fast Matrix Multiplication in Theory

**Best known.**  $O(n^{2.3728596})$  [VW, JA 2020]

**Conjecture.**  $O(n^{2+\varepsilon})$  for any  $\varepsilon > 0$ .

**Caveat.** Theoretical improvements to Strassen are progressively less practical.

They are **galactic algorithms**: the hidden constants by the Big O notation are too **large** so that they outperform any other algorithm for problems that are sufficiently large, but where "**sufficiently large**" is so big that the algorithm is never used in practice. Galactic algorithms were so named by Richard Lipton and Ken Regan,[1] because they will **never be used on any data sets on Earth**.

Eventhough, galactic algorithms may still contribute to computer science:

- may show **new techniques**
- available **computational power** may catch up to the crossover point
- can still **demonstrate** that conjectured bounds can be achieved, or that proposed bounds are wrong, and hence **advance** the theory of algorithms.



# Relazioni di ricorrenza per vari algoritmi

## Divide-et-Impera

- **Dividi** il problema di taglia  $n$  in  $a$  sotto-problemi di taglia  $n/b$
- **Ricorsione** sui sottoproblemi
- **Combinazione** delle soluzioni

$T(n)$  = tempo di esecuzione su input di taglia  $n$

$$T(n) = D(n) + a T(n/b) + C(n)$$

# Alcune relazioni di ricorrenza

Abbiamo considerato una sotto-famiglia

- $T(n) = qT(n/2) + cn$  con  $T(2)=c$

per  $q=1$  allora  $T(n) = O(n)$

$q=2$  allora  $T(n) = O(n \log_2 n)$

$q>2$  allora  $T(n) = O(n^{\log_2 q})$

- $T(n) = 2T(n/2) + cn^2$

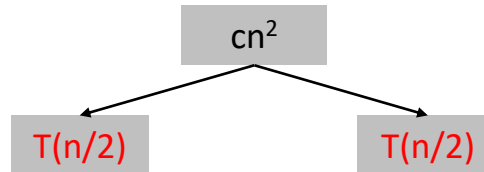
$$T(n) = ?$$

## Albero di ricorsione

$$T(n) = 2 T(n/2) + cn^2$$

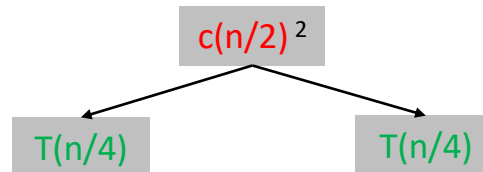
$$T(2) = c$$

Albero per  $T(n)$ :

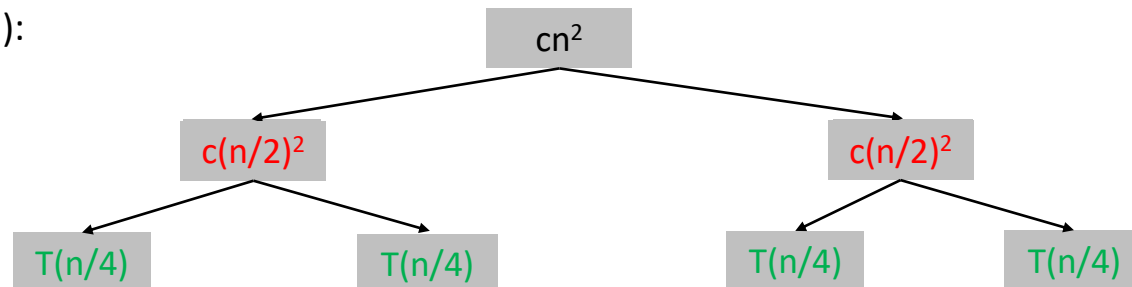


Albero per  $T(n/2)$ :

$$T(n/2) = 2 T(n/4) + c (n/2)^2$$



Albero per  $T(n)$ :



# Albero di ricorsione

$$T(n) = 2 T(n/2) + cn^2$$

$$T(2) = c$$

$i = 0$

$i = 1$

$i = 2$

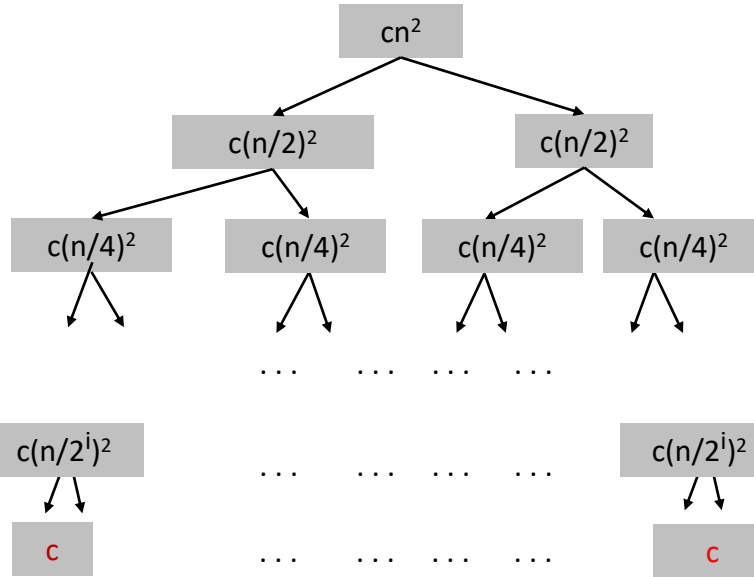
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$i = \log_2 n - 2$

$i = \log_2 n - 1$



$cn^2$

$2c(n/2)^2$

$4c(n/4)^2$

...

$2^i c(n/2^i)^2 = cn^2 / 2^i$

$c (2^{\log_2 n - 1})$

$$T(n) = c (2^{\log_2 n - 1}) + \sum_{i=0}^{\log_2 n - 2} cn^2 / 2^i =$$

$$= c n / 2 + cn^2 \sum_{i=0}^{\log_2 n - 2} (1/2)^i$$

(continua)

$$\begin{aligned} T(n) &= c (2^{\log n - 1}) + \sum_{i=0}^{\log_2 n - 2} cn^2 / 2^i \\ &= c n/2 + c n^2 \sum_{i=0}^{\log_2 n - 2} (1/2)^i \\ &\leq c n/2 + c n^2 \sum_{i=0}^{\infty} (1/2)^i \\ &= c n/2 + 2 c n^2 \end{aligned}$$

$$T(n) = O(n^2)$$

Inoltre dalla definizione  $T(n) \geq cn^2$ . Quindi  $T(n) = \Theta(n^2)$ .



# Altre relazioni di ricorrenza

Abbiamo considerato una sotto-famiglia

- $T(n) = qT(n/2) + cn$  con  $T(2)=c$

per  $q=1$  allora  $T(n) = \Theta(n)$

$q=2$  allora  $T(n) = \Theta(n \log_2 n)$

$q>2$  allora  $T(n) = O(n^{\log_2 q})$

Più in generale.....

- $T(n) = 2T(n/2) + cn^2$

$$T(n) = \Theta(n^2)$$

# Un teorema generale

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Teorema: Se  $n$  é potenza di  $c$ , la soluzione alla ricorrenza

$$T(n) = \begin{cases} d & \text{se } n \leq 1 \\ aT(n/c) + bn & \text{altrimenti} \end{cases}$$

é

$$T(n) = \begin{cases} O(n) & \text{se } a < c \\ O(n \log n) & \text{se } a = c \\ O(n^{\log_c a}) & \text{se } a > c \end{cases}$$

Esempi:

- Se  $T(n) = 2T(n/3) + dn$ , allora  $T(n) = O(n)$
- Se  $T(n) = 2T(n/2) + dn$ , allora  $T(n) = O(n \log n)$
- Se  $T(n) = 4T(n/2) + dn$ , allora  $T(n) = O(n^2)$

Nota: Slide precedente per  $c=2$ ;  $a=q$  (libro [KT]) .

Teorema: Se  $n$  è potenza di  $c$ , la soluzione alla ricorrenza

$$T(n) = \begin{cases} d & \text{se } n \leq 1 \\ aT(n/c) + bn & \text{altrimenti} \end{cases}$$

è

$$T(n) = \begin{cases} O(n) & \text{se } a < c \\ O(n \log n) & \text{se } a = c \\ O(n^{\log_c a}) & \text{se } a > c \end{cases}$$

Esempi:

- Se  $T(n) = 2T(n/3) + dn$ , allora  $T(n) = O(n)$
- Se  $T(n) = 2T(n/2) + dn$ , allora  $T(n) = O(n \log n)$
- Se  $T(n) = 4T(n/2) + dn$ , allora  $T(n) = O(n^2)$

Università degli Studi di Salerno – Corso di Algoritmi – Prof. Ugo Vaccaro – Anno Acc. 2009/10 – p. 9/19

## Esempi

Sia  $T(1) = 1$ . Valutiamo

$$\bullet T(n) = 2T(n/2) + 6n \quad T(n) = O(n \log n)$$

$$\bullet T(n) = 3T(n/3) + 6n - 9 \quad T(n) = O(n \log n)$$

$$\bullet T(n) = 2T(n/3) + 5n \quad T(n) = O(n)$$

$$\bullet T(n) = 2T(n/3) + 12n + 16 \quad T(n) = O(n)$$

$$\bullet T(n) = 4T(n/2) + n \quad T(n) = O(n^{\log_2 4}) = O(n^2)$$

$$\bullet T(n) = 3T(n/2) + 9n \quad T(n) = O(n^{\log_2 3}) = O(n^{1.584...})$$

Più in generale.....

# Master Theorem

facoltativo

Per forme **ancora** più generali del Teorema, che permettono la risoluzione di equazioni di ricorrenza del tipo generale

$$T(n) = aT(n/b) + f(n)$$

sussiste il seguente risultato

1. Se  $f(n) = O(n^{\log_b a - \epsilon})$ , per qualche  $\epsilon > 0$ , allora  $T(n) = \Theta(n^{\log_b a})$
2. Se  $f(n) = \Theta(n^{\log_b a})$ , allora  $T(n) = \Theta(n^{\log_b a} \log n)$
3. Se  $f(n) = \Omega(n^{\log_b a + \epsilon})$ , per qualche  $\epsilon > 0$ , e se  $af(n/b) \leq cf(n)$  per qualche costante  $c < 1$  e  $n$  sufficientemente grande, allora  $T(n) = \Theta(f(n))$

**Nota:** Vale anche con parte intera inferiore o superiore di  $n/b$   
La soluzione  $T(n)$  è in notazione  $\Theta$

# Applicazioni del Master Theorem

$$T(n) = aT(n/b) + f(n)$$

1. Se  $f(n) = O(n^{\log_b a - \epsilon})$ , per qualche  $\epsilon > 0$ , allora  $T(n) = \Theta(n^{\log_b a})$
2. Se  $f(n) = \Theta(n^{\log_b a})$ , allora  $T(n) = \Theta(n^{\log_b a} \log n)$
3. Se  $f(n) = \Omega(n^{\log_b a + \epsilon})$ , per qualche  $\epsilon > 0$ , e se  $af(n/b) \leq cf(n)$  per qualche costante  $c < 1$  e  $n$  sufficientemente grande, allora  $T(n) = \Theta(f(n))$

Confrontare  $f(n)$  con  $n^{\log_b a}$ : qual è «più grande»?

**Il più grande (asintoticamente e polinomialmente) vince!**

**Esempio 1:**  $T(n) = 2T(n/2) + \log n$ :  $a = b = 2$ ,  $f(n) = \log n$  vs  $n^{\log_b a} = n^{\log_2 2} = n^1$   
 $f(n) = O(n^{1-\epsilon})$  per  $\epsilon = 1/2$ , quindi  $T(n) = \Theta(n)$

**Esempio 2:**  $T(n) = 2T(n/2) + n$ :  $a = b = 2$ ,  $f(n) = n$  vs  $n^{\log_b a} = n^{\log_2 2} = n^1$   
 $f(n) = \Theta(n)$ , quindi  $T(n) = \Theta(n \log n)$

**Esempio 3:**  $T(n) = 2T(n/2) + n^3$ :  $a = b = 2$ ,  $f(n) = n^3$  vs  $n^{\log_b a} = n^{\log_2 2} = n^1$   
 $f(n) = \Omega(n^{1+\epsilon})$  e inoltre  $2(n/2)^3 \leq cn^3$  per  $c = 1/4 < 1$   
quindi  $T(n) = \Theta(n^3)$

## Caso di non applicabilità

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

$$a = b = 2,$$

$$f(n) = n \log n \quad \text{vs} \quad n^{\log_b a} = n^{\log_2 2} = n^1$$

$f(n) = n \log n = \Omega(n^1)$ , ma **non esiste** nessun  $\varepsilon$  per cui  $f(n) = \Omega(n^{1+\varepsilon})$

Il Master Theorem **non si applica** a questa relazione di ricorrenza;  
bisogna applicare gli altri metodi

# Altri esempi

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Sia  $T(1) = 1$ . Valutate

- $T(n) = 2T(n/2) + n^3$
- $T(n) = T(9n/10) + n$
- $T(n) = 16T(n/4) + n^2$
- $T(n) = 7T(n/3) + n^2$
- $T(n) = 7T(n/2) + n^2$
- $T(n) = 2T(n/3) + \sqrt{n}$
- $T(n) = T(n-1) + n$
- $T(n) = T(\sqrt{n}) + 1$

## Occorrenze consecutive di 2 (D&I) (dalla piattaforma)

Si scriva lo pseudo-codice di un algoritmo ricorsivo basato sulla tecnica **Divide et Impera** che prende in input un array di interi positivi e restituisce il **massimo** numero di occorrenze **consecutive** del numero '2'.

Ad esempio, se l'array contiene la sequenza <2 2 3 6 2 2 2 2 3 3> allora l'algoritmo restituisce 4.

Occorre specificare l'input e l'output dell'algoritmo.