



Computational complexity

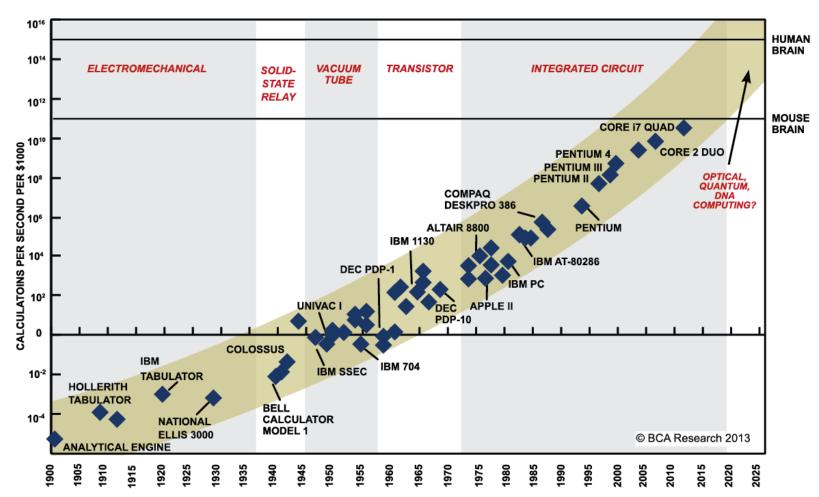
How to measure the difficulty of a problem

How to Measure Efficiency?

- Critical resources
 - programmer's effort
 - time, space (disk, RAM)
- Analysis
 - empirical (run programs)
 - analytical (asymptotic algorithm analysis)
- Worst case vs. Average case

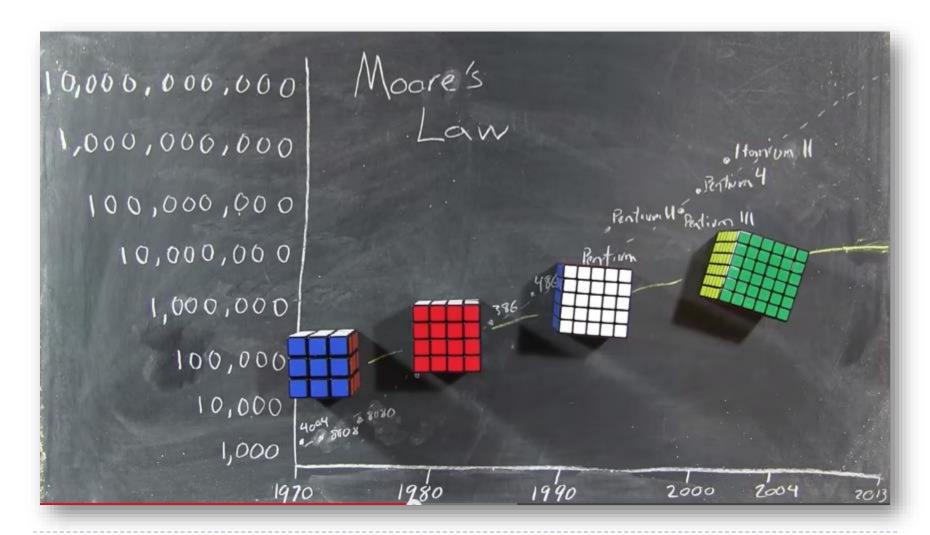


Moore's "Law"?



SOURCE: RAY KURZWEIL, "THE SINGULARITY IS NEAR: WHEN HUMANS TRANSCEND BIOLOGY", P.67, THE VIKING PRESS, 2006. DATAPOINTS BETWEEN 2000 AND 2012 REPRESENT BCA ESTIMATES.

Moore's "Law"?



Sudoku

Е	2			7																													
5	3		Ш	/				L	ᆜ			F	1		_	Б	<u> </u>	0				1.1	17	_	Б			$\overline{}$		_	ΙŦ		
6			1	9	5			l	⊢		V	F	L		L	P	J	S	H			Н	Υ	Ļ	R		-	$\vdash\vdash$		\vdash	T	Q	0
Ě		$\overline{}$	-	_	Ě	\vdash	_	⊢	F	_	X	M P		_		-			\vdash		-			J	Р	Ψ	В	H	C Y		S	┢	Н
	9	8					6	L	D	В	G	_		F	R	_	_	_	_		С			Х	-	L	⊢	Q Y	_	٧	Α	E R	Н
8				6				Γ	⊢	-		Ν		K	Q	<u> -</u>	A M	G	0	s	<u> </u>	F		\vdash	0	V	\vdash	ľ	В	-	W	K.	Н
\vdash	\vdash	-	-	_	_	\vdash	_	H	⊢		V			n	Q	-	S		G	0		Г		⊢	В	٧	\vdash	H	H	L	Υ	К	D
4			8		3			ľ	⊢		٧						9	Q				Υ	U	\vdash	۳	\vdash	\vdash	E	A	\vdash	В	_	W
7	П			2				Г	⊢		Р			М	Α	N	R	K				_	F	s	\vdash	\vdash	Q	-	G	\vdash	۳	\vdash	**
–	\Box		-			\vdash	_	Ľ	⊢	Н	<u>'</u>	D	U	J	F	X	11	В	K		\vdash	W		۲	\vdash	\vdash	-	\vdash	ř	N	E	\vdash	С
	6					2	8	l	⊢	 		۲	ř	Ů	 			P	-	R		M	Т	D	С	\vdash	L	U	H	14	J	\vdash	Ť
			1	1	$\overline{}$			H	⊢		N		Κ		Н			Ė	Н	, ·		1111	P	۲	M	С	-	ŏ	Ŕ	Н	٣	G	Q
			4	1	9			L	Q	\vdash	В	\vdash			V				Х	\vdash	J		Ė	Н	 	s		ĸ	H		М	A	T
				8			7	Ŀ	Ë	U	D				Ė		W	С	H	Ĺ	G	Κ	Α	Q	Υ	Ė		Н	Н		H	Р	H
				•				_	┢	-		Х	Τ	Α		s		-	Н		F		0	Ë	Ū		H	Н	Н	В	F	С	П
									一	G	J		W	L	U	Q								H	٧		R	Н	Е	Ē	-	Х	П
									г		М		N						_		D	Q		Κ		G	S	Р	U	F	П	П	П
									В				Н		Р	D		П		F	Υ	Α	L	Ι		Т		М	П		Н	\vdash	П
									Г	Α		Г		Υ	С			J	Г	U	Г		G	F	Г	Г		П	П		П	Г	П
									Г			Τ					N		W	0	٧		В					Т	П	s	D	Г	П
												С		٧		R		L		Т	Р	N					0	Α	М	Ι		Υ	Κ
									Г	Т			0	Τ					Ν	J		С	R	Г			٧						М
									Υ	N	U				В						Q		Χ			W				Р	С	0	П
											W		М	b		С		٧	Ф	Ρ	Ι					Н		F	D	Κ	Q		
										С		G					Т		ш				М			0		L				٧	Х
									Κ	Х			٧	R	J			F			Н					Q	U			Т		В	

Problems and Algorithms

- We know the efficiency of the solution
- b... but what about the difficulty of the problem?
- Different concepts
 - Algorithm complexity
 - Problem complexity



Analytical Approach

- An algorithm is a mapping
- For most algorithms, running time depends on "size" of the input
- Running time is expressed as T(n)
 - some function T
 - input size n



Bubble sort

unsorted 6 > 1, swap 6 > 2, swap 6 > 3, swap 6 > 4, swap 6 > 5, swap 1 < 2, ok 2 < 3, ok 3 < 4, ok 4 < 5, ok sorted

Analysis

- ▶ The bubble sort takes (n²-n)/2 "steps"
- Different implementations/assembly languages
 - Program A on an Intel Pentium IV: $T(n) = 58*(n^2-n)/2$
 - Program B on a Motorola: $T(n) = 84*(n^2-2n)/2$
 - ▶ Program C on an Intel Pentium V: $T(n) = 44*(n^2-n)/2$
- Note that each has an n² term
 - as n increases, the other terms will drop out



Analysis

As a result:

- ▶ Program A on Intel Pentium IV: $T(n) \approx 29n^2$
- ▶ Program B on Motorola: $T(n) \approx 42n^2$
- ▶ Program C on Intel Pentium V:T(n) $\approx 22n^2$



Analysis

- As processors change, the constants will always change
 - The exponent on n will not
 - We should not care about the constants
- As a result:
 - ▶ Program A:T(n) \approx n²
 - ▶ Program B:T(n) \approx n²
 - ▶ Program C:T(n) ≈ n^2
- ▶ Bubble sort: $T(n) \approx n^2$



Complexity Analysis

- O(·)
 - big o (big oh)
- Ω(·)
 - big omega
- ▶ Θ(·)
 - big theta



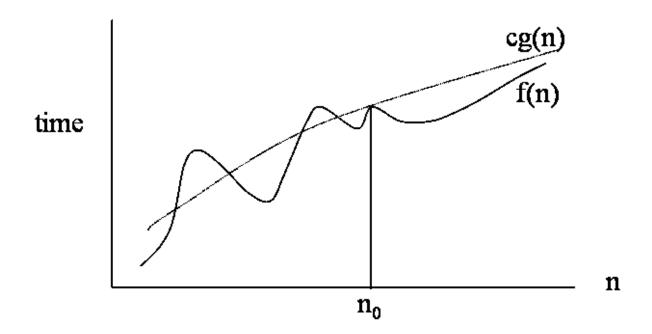
O(·)

- Upper Bounding Running Time
- Why?
 - Little-oh
 - "Order of"
 - ▶ D'Oh



Upper Bounding Running Time

• f(n) is O(g(n)) if f grows "at most as fast as" g



Big-O (formal)

Let f and g be two functions such that

$$f(n): N \to R^+ \text{ and } g(n): N \to R^+$$

▶ if there exists positive constants c and n₀ such that

$$f(n) \le cg(n)$$
, for all $n > n_0$

then we can write

$$f(n) = O(g(n))$$

Big-O (formal alt)

Let f and g be two functions such that

$$f(n): N \to R^+ \text{ and } g(n): N \to R^+$$

▶ if there exists positive constants c and n₀ such that

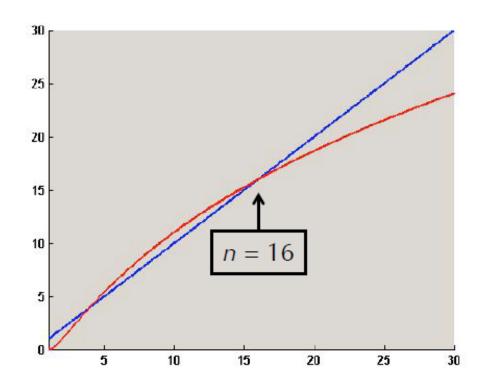
$$0 \le \lim_{n \to \infty} \frac{f(n)}{g(n)} = c < \infty$$

then we can write

$$f(n) = O(g(n))$$

Example

 $| (\log n)^2 = O(n)$



$$f(n) = (\log n)^2$$
$$g(n) = n$$

 $(\log n)^2 \le n$ for all $n \ge 16$, so $(\log n)^2$ is O(n)

Notational Issues

- Big-O notation is a way of <u>comparing</u> functions
- Notation quite unconventional

• e.g.,
$$3x^3 + 5x^2 - 9 = O(x^3)$$

- Doesn't mean
- " $3x^3 + 5x^2 9$ equals the function $O(x^3)$ "
- " $3x^3 + 5x^2 9$ is big oh of x^3 "
- But
 - " $3x^3+5x^2-9$ is dominated by x^3 "

Common Misunderstanding

- $3x^3 + 5x^2 9 = O(x^3)$
- ▶ However, also true are:

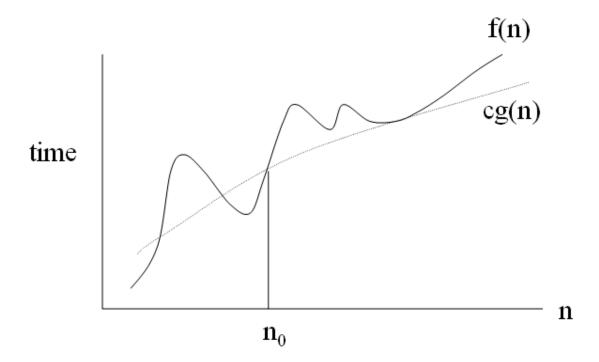
$$3x^3 + 5x^2 - 9 = O(x^4)$$

- $x^3 = O(3x^3 + 5x^2 9)$
- Note:
 - Usage of big-O typically involves mentioning only the most dominant term
 - "The running time is $O(x^{2.5})$ "



Lower Bounding Running Time

• f(n) is $\Omega(g(n))$ if f grows "at least as fast as" g



cg(n) is an approximation to f(n) bounding from below

Big-Omega (formal)

Let f and g be two functions such that

$$f(n): N \to R^+ \text{ and } g(n): N \to R^+$$

▶ if there exists positive constants c and n₀ such that

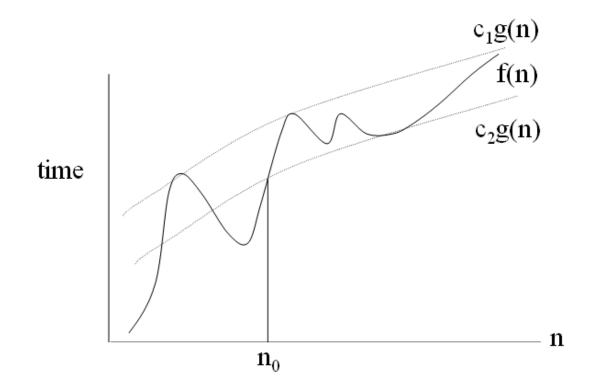
$$f(n) \ge cg(n)$$
, for all $n > n_0$

then we can write

$$f(n) = \Omega(g(n))$$

Tightly Bounding Running Time

• f(n) is $\Theta(g(n))$ if f is essentially the same as g, to within a constant multiple



Big-Theta (formal)

Let f and g be two functions such that

$$f(n): N \to R^+ \text{ and } g(n): N \to R^+$$

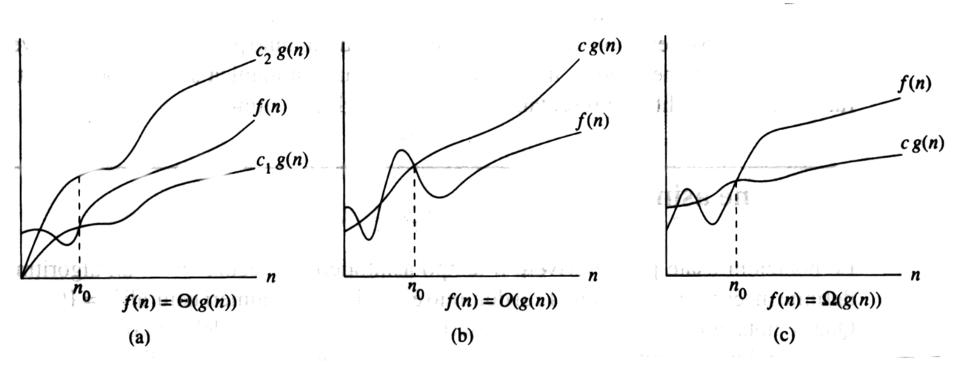
• if there exists positive constants c_1 , c_2 and n_0 such that

$$c_1g(n) \le f(n) \le c_2g(n)$$
, for all $n > n_0$

then we can write

$$f(n) = \Theta(g(n))$$

Big- Θ , Big-O, and Big- Ω



Big- Ω and Big- Θ

▶ Big- Ω : reverse of big-O. I.e.

$$f(x) = \Omega(g(x))$$
iff
$$g(x) = O(f(x))$$

so f(x) asymptotically dominates g(x)

Big- Ω and Big- Θ

▶ Big- Θ : domination in both directions. I.e.

$$f(x) = \Theta(g(x))$$
iff
$$f(x) = O(g(x)) && f(x) = \Omega(g(x))$$

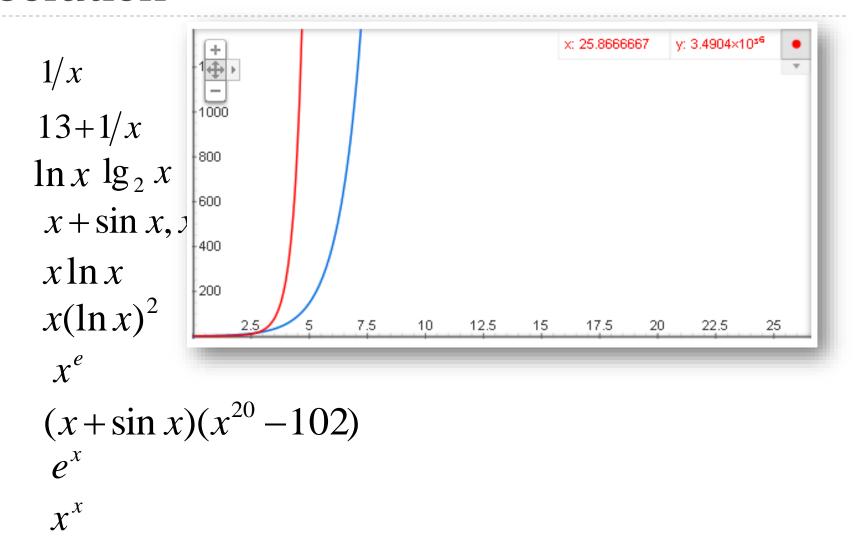
Problem

• Order the following from smallest to largest asymptotically. Group together all functions which are big- Θ of each other:

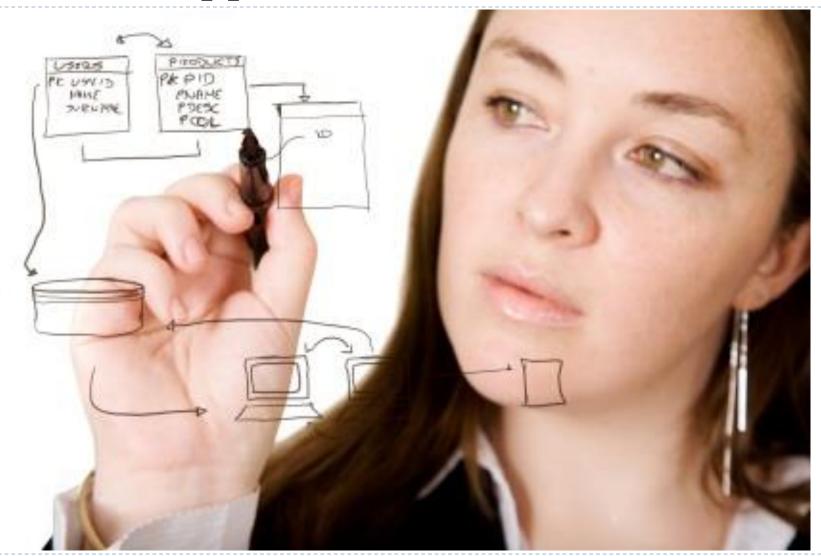
$$x + \sin x, \ln x, x + \sqrt{x}, \frac{1}{x}, 13 + \frac{1}{x}, 13 + x, e^x, x^e, x^x$$

 $(x + \sin x)(x^{20} - 102), x \ln x, x(\ln x)^2, \lg_2 x$

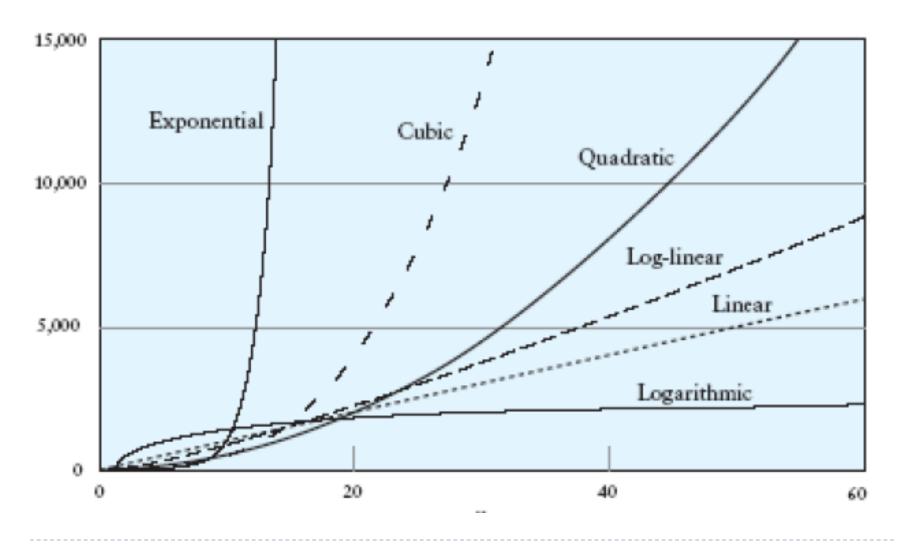
Solution



Practical approach



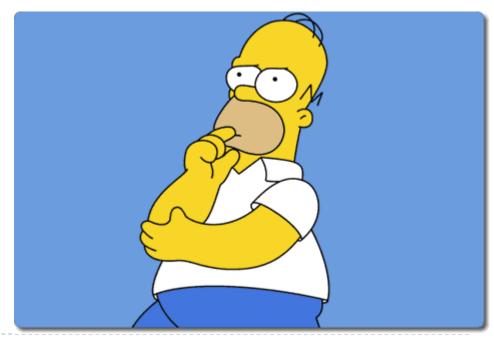
Practical approach



Class C	Complexity	Number	of Operations	and Exec	ution Time (1 in	str/µsec)	
n		10		10	2	10^{3}	
constant	O(1)	1	1 μsec	1	1 μsec	1	1 μsec
logarithimic	$O(\lg n)$	3.32	3 μsec	6.64	7 μsec	9.97	10 μsec
linear	O(n)	10	10 μsec	10^{2}	100 μsec	10^{3}	1 msec
O(n lg n)	$O(n \lg n)$	33.2	33 μsec	664	664 µsec	9970	10 msec
quadratic	$O(n^2)$	10^{2}	100 μsec	104	10 msec	106	1 sec
cubic	$O(n^3)$	10 ³	1 msec	10^{6}	1 sec	10 ⁹	16.7 min
exponential	$O(2^n)$	1024	10 msec	10 ³⁰	3.17 * 10 ¹⁷ yrs	10 ³⁰¹	
n		10^{4}		10	5	10 ⁶	
constant	O(1)	1	1 μsec	1	1 μsec	1	1 μsec
logarithmic	$O(\lg n)$	13.3	13 μsec	16.6	7 μsec	19.93	20 μsec
linear	O(n)	104	10 msec	10 ⁵	0.1 sec	10^{6}	1 sec
$O(n \lg n)$	$O(n \lg n)$	133 * 10 ³	133 msec	166 * 10 ⁴	1.6 sec	199.3 * 10 ⁵	20 sec
quadratic	$O(n^2)$	108	1.7 min	1010	16.7 min	1012	11.6 days
cubic	$O(n^3)$	1012	11.6 days	10 ¹⁵	31.7 yr	10^{18}	31,709 yr
exponential	$O(2^n)$	103010		10 ³⁰¹⁰³		10^{301030}	

Would it be possible?

Algorithm	Foo	Bar
Complexity	O(n ²)	O(2 ⁿ)
n = 100	I Os	4s
n = 1000	I2s	4.5s



Determination of Time Complexity

- Because of the approximations available through Big-Oh, the actual T(n) of an algorithm is not calculated
 - T(n) may be determined empirically
- Big-Oh is usually determined by application of some simple 5 rules

Rule #1

Simple program statements are assumed to take a constant amount of time which is

O(I)

Rule #2

Differences in execution time of simple statements is ignored

Rule #3

In conditional statements the worst case is always used

Rule #4 – the "sum" rule

- The running time of a sequence of steps has the order of the running time of the largest
- ▶ E.g.,
 - $f(n) = O(n^2)$
 - $g(n) = O(n^3)$
 - $f(n) + g(n) = O(n^3)$

Rule #5 – the "product" rule

If two processes are constructed such that second process is repeated a number of times for each n in the first process, then O is equal to the product of the orders of magnitude for both products

▶ E.g.,

- For example, a two-dimensional array has one for loop inside another and each internal loop is executed n times for each value of the external loop.
- ▶ The function is $O(n^2)$

```
for(int t=0; t<n; ++t) {
    for(int u=0; u<n; ++u) {
        ++zap;
    }
}</pre>
O(n*I)
```

```
for(int t=0; t<n; ++t) { O(n)
  for(int u=0; u<n; ++u) {
     ++zap;
  }
}</pre>
```

```
for(int t=0; t<n; ++t) {
    for(int u=0; u<n; ++u) {
        ++zap;
    }
}</pre>
O(n<sup>2</sup>)
```

Note: Running time grows with nesting rather than the length of the code

```
for(int t=0; t<n; ++t) {
    for(int u=0; u<n; ++u) {
        ++zap;
    }
}</pre>
O(n<sup>2</sup>)
```

More Nested Loops

Sequential statements

```
for(int z=0; z<n; ++z)
    zap[z] = 0;

for(int t=0; t<n; ++t) {
    for(int u=t; u<n; ++u) {
        ++zap;
    }
}</pre>
O(n)
```

▶ Running time: $max(O(n), O(n^2)) = O(n^2)$

Conditionals

```
for(int t=0; t<n; ++t) {
   if(t%2) {
      for(int u=t; u<n; ++u) {
        ++zap;
   } else {
     zap = 0; O(I)
```

Conditionals

```
for(int t=0; t<n; ++t) {
   if(t%2) {
      for(int u=t; u<n; ++u) {
         ++zap;
                                  \sim O(n^2)
   } else {
      zap = 0;
```



Tips

- Focus only on the dominant (high cost) operations and avoid a line-by-line exact analysis
- Break algorithm down into "known" pieces
- Identify relationships between pieces
 - Sequential is additive
 - Nested (loop / recursion) is multiplicative
- Drop constants
- Keep only dominant factor for each variable

Caveats

▶ Real time vs. complexity



Tecniche di programmazione A.A. 2017/18

Caveats

- ▶ Real time vs. complexity
- ▶ CPU time vs. RAM vs. disk

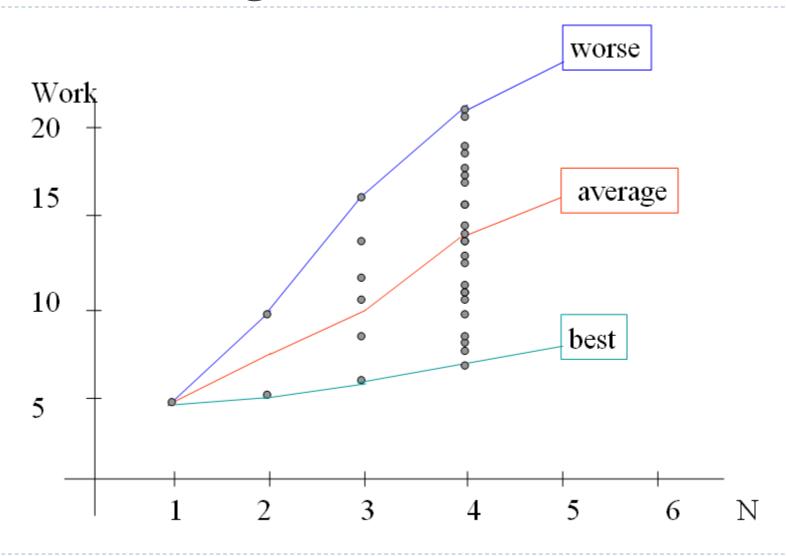


Caveats

- ▶ Real time vs. complexity
- ▶ CPU time vs. RAM vs. disk
- Worse, Average or Best Case?

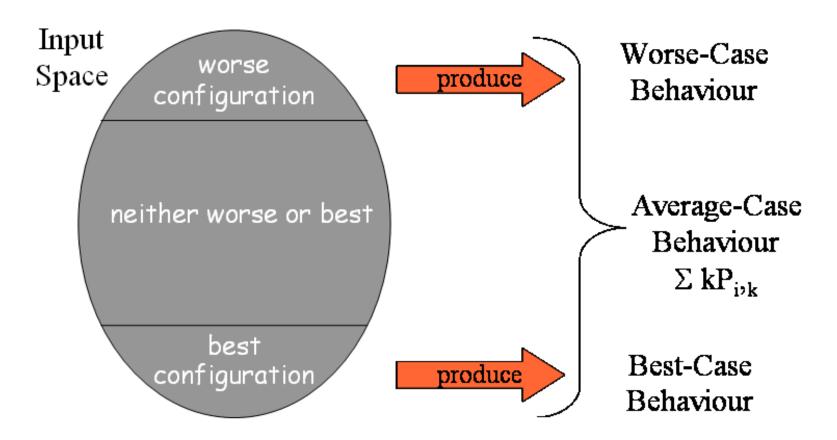


Worse, Average or Best Case?



Worse, Average or Best Case?

Depends on input problem instance type



Computational Complexity Theory

In computer science, computational complexity theory is the branch of the theory of computation that studies the resources, or cost, of the computation required to solve a given computational problem

 Complexity theory analyzes the difficulty of computational problems in terms of many different computational resources

Note

Solve a problem

VS.

Verify a solution

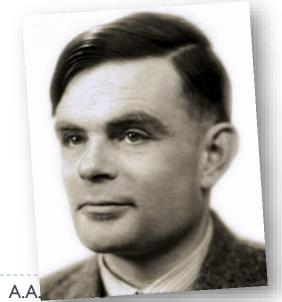
- ▶ E.g.,
 - Sort
 - Shortest path

Complexity Classes

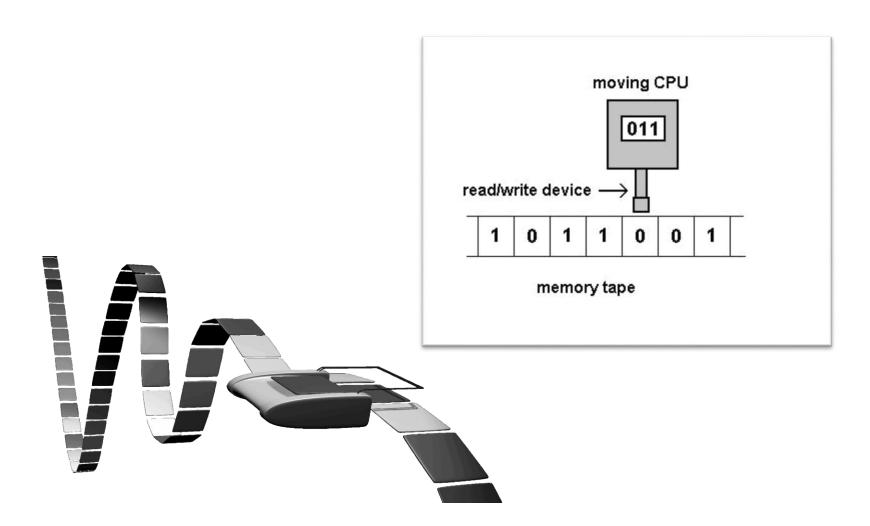
A complexity class is the set of all of the computational problems which can be solved using a certain amount of a certain computational resource

Deterministic Turing Machine

- Deterministic or Turing machines are extremely basic symbol-manipulating devices which — despite their simplicity — can be adapted to simulate the logic of any computer that could possibly be constructed
- Described in 1936 by Alan Turing.
 - Not meant to be a practical computing technology
 - Technically feasible
 - A thought experiment about the limits of mechanical computation

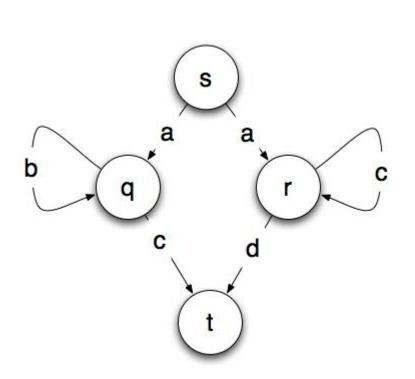


Deterministic Turing Machine

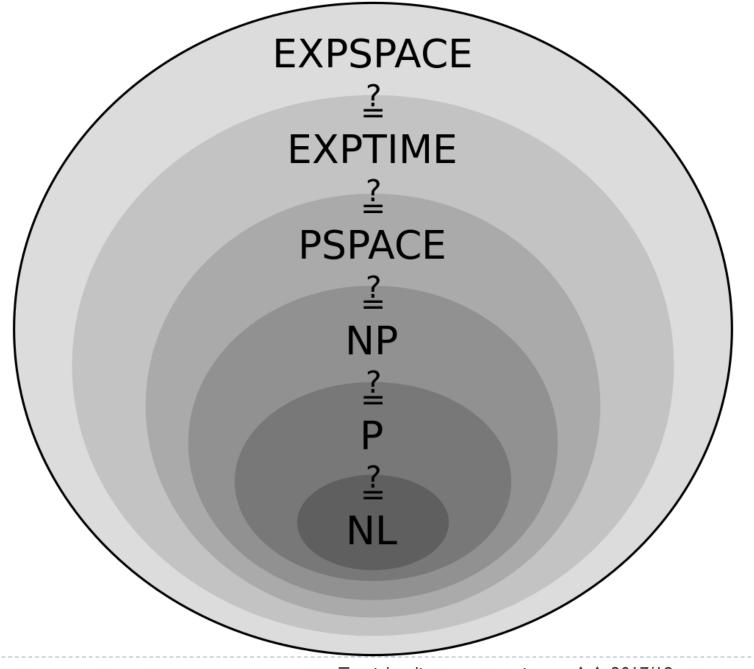


Non-Deterministic Turing Machine

Turing machine whose control mechanism works like a non-deterministic finite automaton







Class	Resource	Model	Constraint
DTIME(f(n))	Time	DTM	f(n)
Р	Time	DTM	$O(n^k)$
EXPTIME	Time	DTM	$O(2^{n^k})$
NTIME	Time	NDTM	f(n)
NP	Time	NDTM	$O(n^k)$
NEXPTIME	Time	NDTM	$O(2^{n^k})$
DSPACE(f(n))	Space	DTM	f(n)
L	Space	DTM	$O(\log(n))$
PSPACE	Space	DTM	$O(n^k)$
EXPSPACE	Space	DTM	$O(2^{n^k})$
NSPACE(f(n))	Space	NDTM	f(n)
NL	Space	NDTM	$O(\log(n))$
NPSPACE	Space	NDTM	$O(n^k)$
NEXPSPACE	Space	NDTM	$O(2^{n^k})$

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration
n	Linear	Algorithm scans its input (at least)

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration
n	Linear	Algorithm scans its input (at least)
nlgn	"n-log-n"	Some divide and conquer

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration
n	Linear	Algorithm scans its input (at least)
nlgn	"n-log-n"	Some divide and conquer
n²	Quadratic	Loop inside loop = "nested loop"

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration
n	Linear	Algorithm scans its input (at least)
nlgn	"n-log-n"	Some divide and conquer
n²	Quadratic	Loop inside loop = "nested loop"
n³	Cubic	Loop inside nested loop

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration
n	Linear	Algorithm scans its input (at least)
nlgn	"n-log-n"	Some divide and conquer
n ²	Quadratic	Loop inside loop = "nested loop"
n³	Cubic	Loop inside nested loop
2 ⁿ	Exponential	Algorithm generates all subsets of n-element set

Class	Name	Comments
1	Constant	Algorithm ignores input (i.e., can't even scan input)
lgn	Logarithmic	Cuts problem size by constant fraction on each iteration
n	Linear	Algorithm scans its input (at least)
nlgn	"n-log-n"	Some divide and conquer
n ²	Quadratic	Loop inside loop = "nested loop"
n ³	Cubic	Loop inside nested loop
2 ⁿ	Exponential	Algorithm generates all subsets of n-element set
n!	Factorial	Algorithm generates all permutations of n-element set

ArrayList vs. LinkedList

	ArrayList	LinkedList
add(element)	O(I)	O(I)
remove(object)	O(n) + O(n)	O(n) + O(1)
get(index)	O (I)	O(n)
set(index, element)	O (I)	O(n) + O(1)
add(index, element)	O(1) + O(n)	O(n) + O(1)
remove(index)	O(n)	O(n) + O(1)
contains(object)	O(n)	O(n)
indexOf(object)	O(n)	O (n)

In theory, there is no difference between theory and practice.



Licenza d'uso



 Queste diapositive sono distribuite con licenza Creative Commons "Attribuzione - Non commerciale - Condividi allo stesso modo (CC BY-NC-SA)"

Sei libero:

- di riprodurre, distribuire, comunicare al pubblico, esporre in pubblico, rappresentare, eseguire e recitare quest'opera

di modificare quest'opera

Alle seguenti condizioni:

Attribuzione — Devi attribuire la paternità dell'opera agli autori originali e in modo tale da non suggerire che essi avallino te o il modo i cui tu usi l'opera.



- Non commerciale Non puoi usare quest'opera per fini commerciali.
- Condividi allo stesso modo Se alteri o trasformi quest'opera, o se la usi per crearne un'altra, puoi distribuire l'opera risultante solo con ur licenza identica o equivalente a questa.
- http://creativecommons.org/licenses/by-nc-sa/3.0/