

Runtime Complexity



CS 331: Data Structures and Algorithms

So far, our runtime analysis has been based on *empirical evidence*

- i.e., runtimes obtained from actually running our algorithms



But measured runtime is very sensitive to:

- platform (OS/compiler/interpreter)
- concurrent tasks
- implementation details (vs. high-level algorithm)



And measured runtime doesn't always
help us see *long-term / big picture trends*



Reframing the problem:

Given an algorithm that takes *input size* n , we want a function $T(n)$ that describes the *running time* of the algorithm



input size might be the *number of items* in the input (e.g., as in a list), or the *magnitude of the input value* (e.g., for numeric input).

an algorithm may also be dependent on the size of *more than one input*.



```
def sort(vals):  
    # input size = len(vals)
```

```
def factorial(n):  
    # input size = n
```

```
def gcd(m, n):  
    # input size = (m, n)
```



running time is based on # of *primitive operations* (e.g., statements, computations) carried out by the algorithm.

ideally, machine independent!



	<i>cost</i>	<i>times</i>
<code>def factorial(n):</code>		
<code>prod = 1</code>	c_1	1
<code>for k in range(2, n+1):</code>	c_2	$n - 1$
<code>prod *= k</code>	c_3	$n - 1$
<code>return prod</code>	c_4	1

$$T(n) = c_1 + (n - 1)(c_2 + c_3) + c_4$$

Messy! Per-instruction costs obscure the “big picture” runtime function.



```

def factorial(n):                                times
    prod = 1 ..... 1
    for k in range(2, n+1): .....  $n - 1$ 
        prod *= k .....  $n - 1$ 
    return prod ..... 1

```

$$T(n) = 2(n - 1) + 2 = 2n$$

Simplification #1: ignore actual cost of each line of code.

Runtime is *linear* w.r.t. input size.



Next: a sort algorithm — *insertion* sort

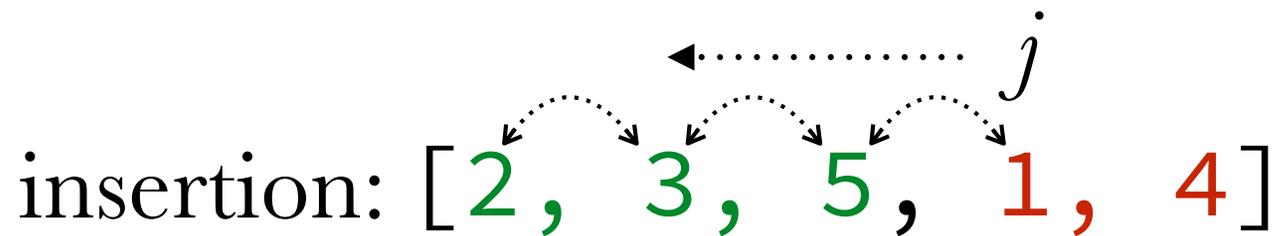
Inspiration: sorting a hand of cards



i ▶

init: [5, 2, 3, 1, 4]

insertion: [2, 3, 5, 1, 4]



```
def insertion_sort(lst):  
    for i in range(1, len(lst)):  
        for j in range(i, 0, -1):  
            if lst[j] < lst[j-1]:  
                lst[j], lst[j-1] = lst[j-1], lst[j]  
            else:  
                break
```



```

def insertion_sort(lst):                                     times
    for i in range(1, len(lst)): .....  $n - 1$ 
        for j in range(i, 0, -1): ..... ?
            if lst[j] < lst[j-1]: ..... ?
                lst[j], lst[j-1] = lst[j-1], lst[j] .. ?
            else: ..... ?
                break ..... ?

```

?’s will vary based on initial “sortedness”
 ... useful to contemplate *worst case scenario*



```

def insertion_sort(lst):
    for i in range(1, len(lst)):
        for j in range(i, 0, -1):
            if lst[j] < lst[j-1]:
                lst[j], lst[j-1] = lst[j-1], lst[j]
            else:
                break

```

times

..... $n - 1$

..... ?

..... ?

..... ?

..... ?

..... ?

worst case arises when list values start out
in *reverse order*!



```

def insertion_sort(lst):
    for i in range(1, len(lst)):
        for j in range(i, 0, -1):
            if lst[j] < lst[j-1]:
                lst[j], lst[j-1] = lst[j-1], lst[j]
            else:
                break

```

times

..... $n - 1$

..... $1, 2, \dots, (n - 1)$

..... $1, 2, \dots, (n - 1)$

..... $1, 2, \dots, (n - 1)$

..... 0

..... 0

worst case analysis — this is our default
analysis hereafter unless otherwise noted



Review (or crash course) on *arithmetic series*

e.g., $1+2+3+4+5 (=15)$

Sum can also be found by:

- adding first and last term ($1+5=6$)
- dividing by two (find average) ($6/2=3$)
- multiplying by num of values ($3\times 5=15$)



$$\text{i.e., } 1 + 2 + \cdots + n = \sum_{t=1}^n t = \frac{n(n+1)}{2}$$

$$\text{and } 1 + 2 + \cdots + (n-1) = \sum_{t=1}^{n-1} t = \frac{(n-1)n}{2}$$



```

def insertion_sort(lst):
    for i in range(1, len(lst)):
        for j in range(i, 0, -1):
            if lst[j] < lst[j-1]:
                lst[j], lst[j-1] = lst[j-1], lst[j]
            else:
                break

```

times

	$n - 1$
	$1, 2, \dots, (n - 1)$
	$1, 2, \dots, (n - 1)$
	$1, 2, \dots, (n - 1)$
	0
	0



<code>def insertion_sort(lst):</code>	<i>times</i>
<code>for i in range(1, len(lst)):</code>	$n - 1$
<code>for j in range(i, 0, -1):</code>	$\sum_{t=1}^{n-1} t$
<code>if lst[j] < lst[j-1]:</code>	$\sum_{t=1}^{n-1} t$
<code>lst[j], lst[j-1] = lst[j-1], lst[j]</code>	$\sum_{t=1}^{n-1} t$
<code>else:</code>	0
<code>break</code>	0



```

def insertion_sort(lst):                                     times
    for i in range(1, len(lst)): ..... n - 1
        for j in range(i, 0, -1): ..... (n - 1)n/2
            if lst[j] < lst[j-1]: ..... (n - 1)n/2
                lst[j], lst[j-1] = lst[j-1], lst[j] .. (n - 1)n/2
            else: ..... 0
                break ..... 0

```

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



$$T(n) = \frac{3}{2}n^2 - \frac{n}{2} - 1$$

i.e., runtime of insertion sort is a *quadratic function* of its input size.

Simplification #2: only consider *leading term*; i.e., with the *highest order of growth*

Simplification #3: *ignore constant coefficients*



$$T(n) = \frac{3}{2}n^2 - \frac{n}{2} - 1$$

... we conclude that insertion sort has a *worst-case runtime complexity* of n^2

we write: $T(n) = O(n^2)$

read: “is big-O of”



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

means that there exists constants c, n_0

such that $0 \leq f(n) \leq c \cdot g(n)$

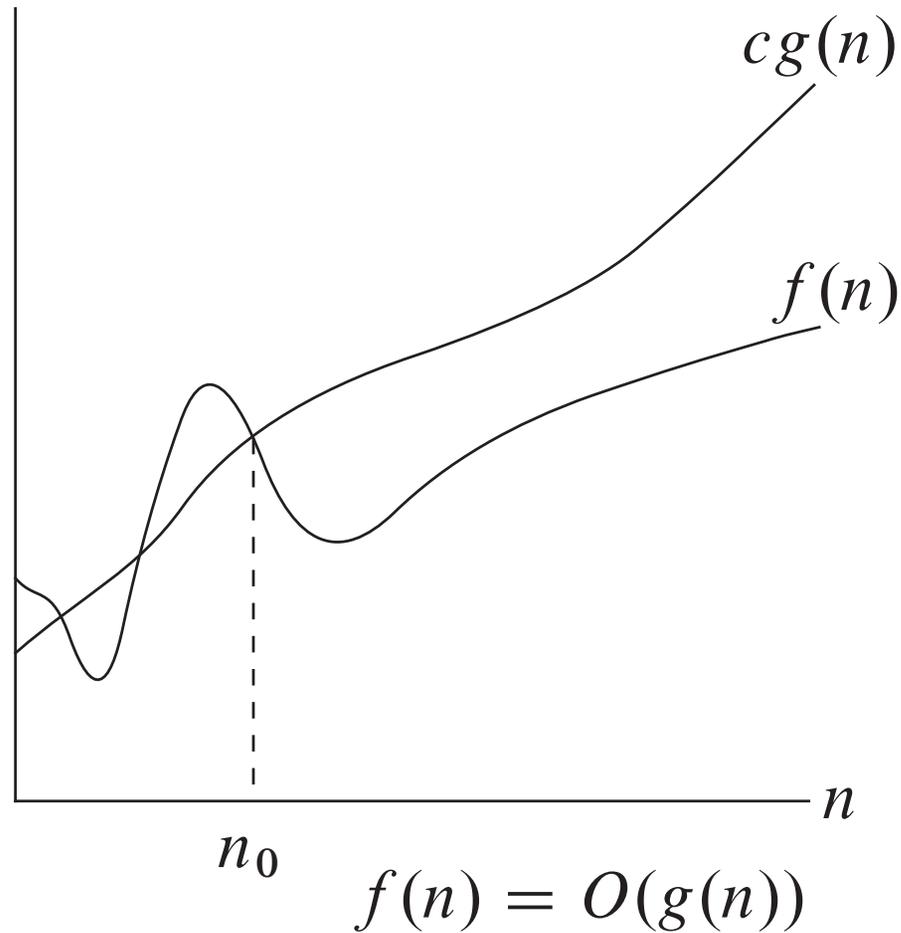
for all $n \geq n_0$



i.e., $f(n) = O(g(n))$

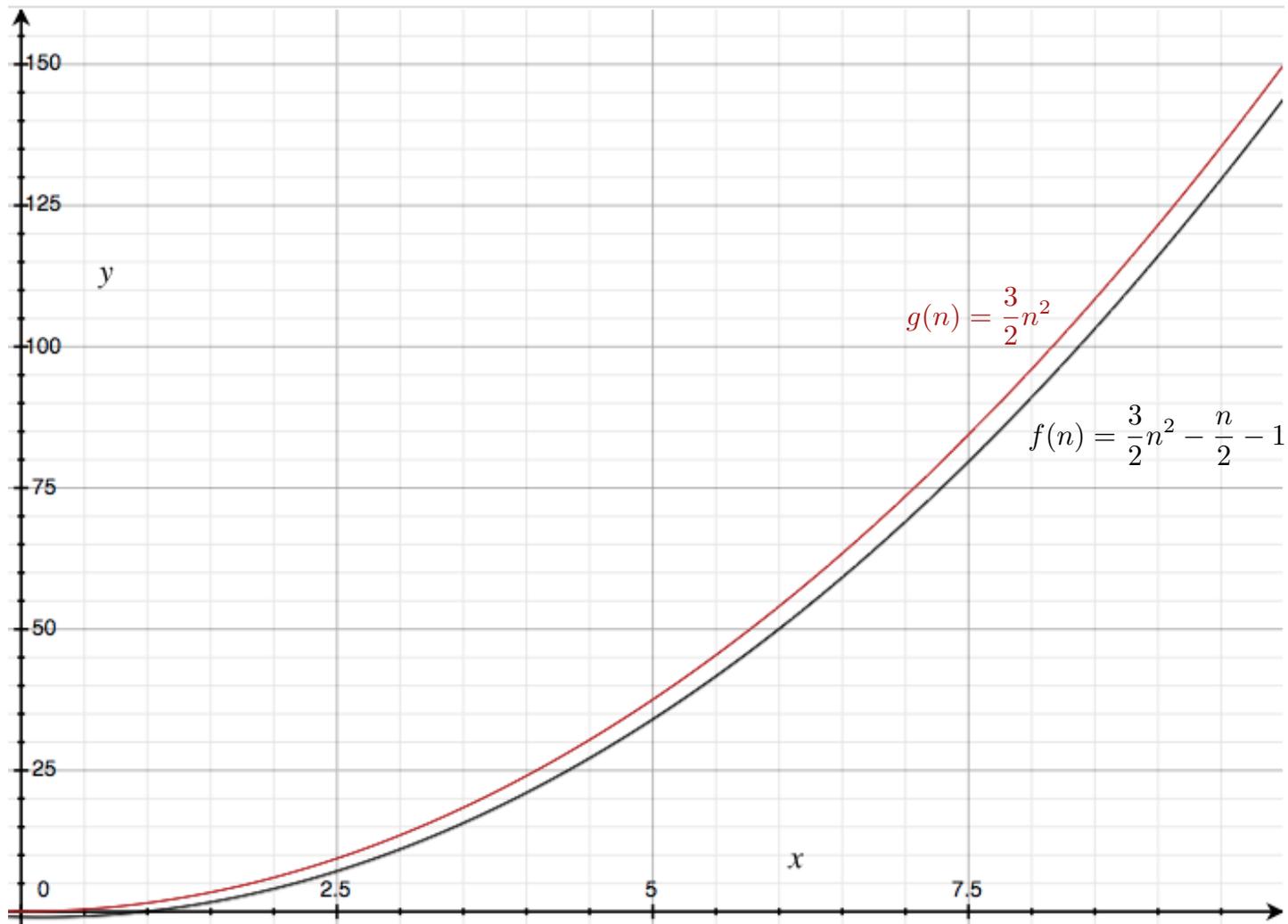
intuitively means that g (multiplied by a constant factor) sets an *upper bound* on f as n gets large — i.e., an *asymptotic bound*





(from Cormen, Leiserson, Riest, and Stein, Introduction to Algorithms)





technically, $f = O(g)$ does not imply a
asymptotically *tight bound*

e.g., $n = O(n^2)$ is true, but there is no
constant c such that cn^2 will approximate
the growth of n , as n gets large



but in this class we *will* use big-O notation to signify asymptotically tight bounds

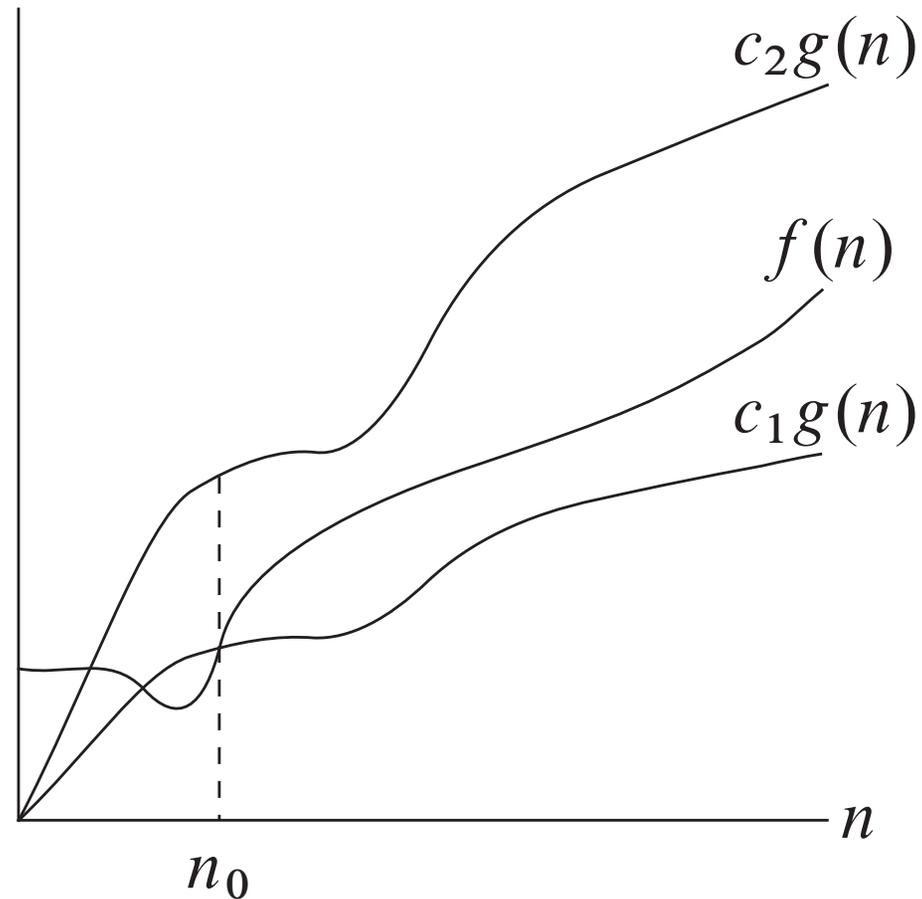
i.e., there are constants c_1, c_2 such that:

$$c_1 g(n) \leq f(n) \leq c_2 g(n), \text{ for } n \geq n_0$$

(there's another notation: Θ — big-theta — but we're avoiding the formalism)



asymptotically tight bound: g “sandwiches” f



(from Cormen, Leiserson, Riest, and Stein, Introduction to Algorithms)



So far, we've seen:

- binary search = $O(\log n)$
- factorial, linear search = $O(n)$
- insertion sort = $O(n^2)$



```
def quadratic_roots(a, b, c):  
    discr = b**2 - 4*a*c  
    if discr < 0:  
        return None  
    discr = math.sqrt(discr)  
    return (-b+discr)/(2*a), (-b-discr)/(2*a)
```

$$= O(?)$$



```
def quadratic_roots(a, b, c):  
    discr = b**2 - 4*a*c  
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```

Always a *fixed (constant) number* of LOC executed, regardless of input.

$$= O(?)$$



```
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    return (-b+discr)/(2*a), (-b-discr)/(2*a)
```

Always a *fixed (constant) number* of LOC executed, regardless of input.

$$T(n) = C = O(1)$$



```
def foo(m, n):  
    for _ in range(m):  
        for _ in range(n):  
            pass
```

$= O(?)$



```
def foo(m, n):  
    for _ in range(m):  
        for _ in range(n):  
            pass
```

$$= O(m \times n)$$



```
def foo(n):  
    for _ in range(n):  
        for _ in range(n):  
            for _ in range(n):  
                pass
```

$= O(?)$



```
def foo(n):  
    for _ in range(n):  
        for _ in range(n):  
            for _ in range(n):  
                pass
```

$$= O(n^3)$$



$$\begin{bmatrix} a_{00} & a_{01} & a_{02} \\ a_{10} & a_{11} & a_{12} \\ a_{20} & a_{21} & a_{22} \end{bmatrix} \times \begin{bmatrix} b_{00} & b_{01} & b_{02} \\ b_{10} & b_{11} & b_{12} \\ b_{20} & b_{21} & b_{22} \end{bmatrix} = \begin{bmatrix} c_{00} & c_{01} & c_{02} \\ c_{10} & c_{11} & c_{12} \\ c_{20} & c_{21} & c_{22} \end{bmatrix}$$

$$c_{ij} = a_{i0}b_{0j} + a_{i1}b_{1j} + \cdots + a_{in}b_{nj}$$

i.e., for $n \times n$ input matrices, each result cell requires n multiplications



```
def square_matrix_multiply(a, b):  
    dim = len(a)  
    c = [[0] * dim for _ in range(dim)]  
    for row in range(dim):  
        for col in range(dim):  
            for i in range(dim):  
                c[row][col] += a[row][i] * b[i][col]  
    return c
```

$$= O(dim^3)$$



using “brute force” to
crack an n -bit password $= O(?)$



1 character (8 bits)
(2^8 possible values)

00000000
00000001
00000010
00000011
00000100
00000101
00000110
00000111
00001000
00001001
00001010
00001011
00001100
00001101
00001110
...
11110010
11110011
11110100
11110101
11110110
11110111
11111000
11111001
11111010
11111011
11111100
11111101
11111110
11111111

= $O(?)$



using “brute force” to
crack an n -bit password $= O(2^n)$



Name	Class	Example
Constant	$O(1)$	Compute discriminant
Logarithmic	$O(\log n)$	Binary search
Linear	$O(n)$	Linear search
Linearithmic	$O(n \log n)$	Heap sort (coming!)
Quadratic	$O(n^2)$	Insertion sort
Cubic	$O(n^3)$	Matrix multiplication
Polynomial	$O(n^c)$	Generally, c nested loops over n items
Exponential	$O(c^n)$	Brute forcing an n -bit password
Factorial	$O(n!)$	“Traveling salesman” problem

Common order of growth classes

