

## Ch 16.3 Algorithm analysis

Estimate the efficiency of an algorithm. Usually measuring time and space.

There's a BIG difference between measuring performance for algorithms vs. programs.

- ❖ Algorithms - theoretical calculation, estimates, performance in the limit, average vs. worst case analysis, no accounting for implementation factors
- ❖ Programs - measuring actual runtimes, language specific, implementation specific, includes many "reality" factors

Definitions

**Basic step/operation** - an algorithm step that is simple and executes in constant time

**Complexity analysis** - estimate of the basic steps in an algorithm to process a problem of size N; common to have two kinds of complexity analysis: worst-case and average-case

**Asymptotic complexity** - complexity analysis as problem size (N) gets large; this represents the general case

### Big O notation

- Describes algorithm complexity at the limit as N approaches infinity
- Strip out constants and other terms overwhelmed as N gets large; example:  $5n^2 + 10n + 7$  is  $O(n^2)$
- Binary search is  $O(\log n)$ ; this is pronounced "Big Oh of log N"
- "a computational problem is said to be in  $O(g(n))$  if there exists an algorithm for the problem whose worst case complexity function is in  $O(g(n))$ "... page 995

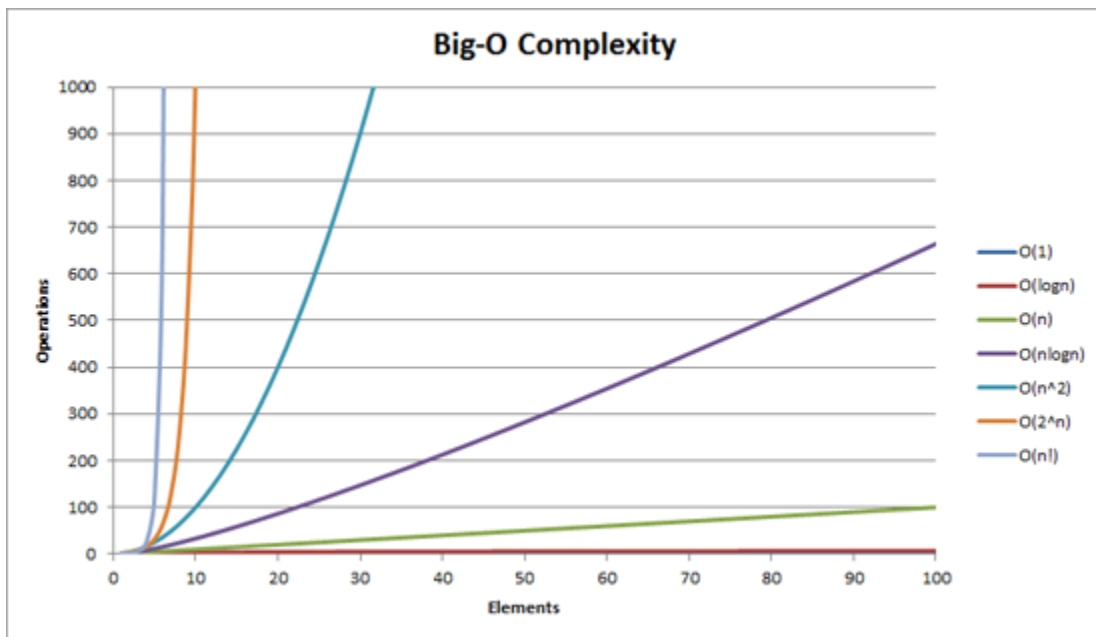
This table is an expansion on the list on page 995 in our text:

Name	Big-O	Description/Example
constant time	$O(1)$	Run time is essentially independent of problem size Example: hash table lookup
logarithmic time	$O(\log n)$	Run time increases slowly as problem size increases Example: Binary search
linear time	$O(n)$	Run time increases directly along with problem size Example: Sequential search
"n log n" time	$O(n \cdot \log n)$	Run time increases slightly faster Example: Quicksort
quadratic time	$O(n^2)$	Run time increases as a square of the problem size. Example: Bubble sort, nested loops

polynomial time	$O(n^c)$ where $c \geq 1$	Union of all algorithms that perform at $O(n)$ , $O(n^2)$ , $O(n^3)$ , ...
exponential time	$O(c^n)$ where $c >$	Run time increases very rapidly as problem size increases. Example: Travelling salesman problem
factorial time	$O(n!)$	Run time explodes. $20! = 10^{18}$ . Example: Brute force travelling salesman

### Big-O Complexity Classes

Source: [www.daveperrett.com/articles/2010/12/07/comp-sci-101-big-o-notation/](http://www.daveperrett.com/articles/2010/12/07/comp-sci-101-big-o-notation/)



Big-O	Operations for 10 "things"	Operations for 100 "things"
$O(1)$	1	1
$O(\log n)$	3	7
$O(n)$	10	100
$O(n \log n)$	30	700
$O(n^2)$	100	10000
$O(2^n)$	1024	$2^{100}$
$O(n!)$	3628800	100!

Even 100 "things" is tiny. What if your algorithm has to process 100K "things"?