Analysis

• How to reason about the performance of algorithms
Defining Efficiency

“Runs fast on typical real problem instances”

Pro:
    sensible, bottom-line-oriented

Con:
    moving target (diff computers, compilers)
    highly subjective (how fast is “fast”? What’s “typical”?)
Efficiency

We want a general theory of “efficiency” that is:

Simple
Objective
Relatively independent of changing technology
But still predictive – “theoretically bad” algorithms should be bad in practice and vice versa
Measuring efficiency

Time: # of instructions executed in a simple programming language
  only simple operations (+,*,=-,if,call,…)
  each operation takes one time step
  each memory access takes one time step
  no fancy stuff (add these two matrices, copy this long string,…) built in; write it/charge for it as above
We left out things but...

Things we’ve dropped
  memory hierarchy
    disk, caches, registers have many orders of magnitude differences in access time
  not all instructions take the same time in practice (+, ÷)
communication
  different computers have different primitive instructions

However,
  one can usually tune implementations so that the hierarchy, etc., is not a huge factor
Problem

• Algorithms can have different running times on different inputs!
• Smaller inputs take less time, larger inputs take more time.
Solution

Measure performance on problem size $n$

Average-case complexity: avg # steps algorithm takes on inputs of size $n$

Worst-case complexity: max # steps algorithm takes on any input of size $n$
Pros and cons:

Average-case
- over what probability distribution? (different settings may have different “average” problems)
- analysis often hard

Worst-case
+ a fast algorithm has a comforting guarantee
+ analysis easier
+ useful in real-time applications (space shuttle, nuclear reactors)
- may be too pessimistic
General Goals

Characterize *growth rate* of (worst-case) run time as a function of problem size, up to a constant factor

Why not try to be more precise?
   - Technological variations (computer, compiler, OS, …) easily 10x or more
Complexity

The *complexity* of an algorithm associates a number $T(n)$, the worst-case time the algorithm takes on problems of size $n$, with each problem size $n$.

Mathematically,

$T: N^+ \rightarrow R^+$

i.e., $T$ is a function that maps positive integers (problem sizes) to positive real numbers (number of steps).
Complexity

Time

Problem size

T(n)
Complexity

- $n \log_2 n$
- $2n \log_2 n$

**Problem size** vs. **Time**

$T(n)$
O-notation, etc.

Given two functions $f$ and $g: \mathbb{N} \rightarrow \mathbb{R}$

- $f(n)$ is $O(g(n))$ iff there is a constant $c > 0$ so that $f(n)$ is eventually always $< c \cdot g(n)$

- $f(n)$ is $\Omega(g(n))$ iff there is a constant $c > 0$ so that $f(n)$ is eventually always $> c \cdot g(n)$

- $f(n)$ is $\Theta(g(n))$ iff there are constants $c_1, c_2 > 0$ so that eventually always $c_1 g(n) < f(n) < c_2 g(n)$
Examples

$10n^2 - 16n + 100$ is $O(n^2)$ also $O(n^3)$

$10n^2 - 16n + 100 < 10n^2$ for all $n > 10$

$10n^2 - 16n + 100$ is $\Omega(n^2)$ also $\Omega(n)$

$10n^2 - 16n + 100 > 9n^2$ for all $n > 16$

Therefore also $10n^2 - 16n + 100$ is $\Theta(n^2)$

$10n^2 - 16n + 100$ is not $O(n)$ also not $\Omega(n^3)$
Properties

Transitivity.
- If \( f = O(g) \) and \( g = O(h) \) then \( f = O(h) \).
- If \( f = \Omega(g) \) and \( g = \Omega(h) \) then \( f = \Omega(h) \).
- If \( f = \Theta(g) \) and \( g = \Theta(h) \) then \( f = \Theta(h) \).

Additivity.
- If \( f = O(h) \) and \( g = O(h) \) then \( f + g = O(h) \).
- If \( f = \Omega(h) \) and \( g = \Omega(h) \) then \( f + g = \Omega(h) \).
- If \( f = \Theta(h) \) and \( g = \Theta(h) \) then \( f + g = \Theta(h) \).
Asymptotic Bounds for Some Common Functions

Polynomials:
\[ a_0 + a_1 n + \ldots + a_d n^d \] is \( \Theta(n^d) \) if \( a_d > 0 \)

Logarithms:
\[ \log_a n = \Theta(\log_b n) \] for any constants \( a, b > 1 \)

Logarithms:
For all \( x > 0 \), \( \log n = O(n^x) \)

\( \log \) grows slower than every polynomial
“One-Way Equalities”

2 + 2 is 4  
2 + 2 = 4  
4 = 2 + 2  

2n^2 + 5 n is O(n^3)  
2n^2 + 5 n = O(n^3)  
O(n^3) = 2n^2 + 5 n  

Bottom line:  
OK to put big-O in R.H.S. of equality, but not left.  
[Better, but uncommon, notation: T(n) < O(f(n)).]
Big-Theta, etc. not always “nice”

\[ f(n) = \begin{cases} 
  n^2, & n \text{ even} \\
  n, & n \text{ odd} 
\end{cases} \]

\( f(n) \) is not \( \Theta(n^a) \) for any \( a \).

Fortunately, such nasty cases are rare
Asymptotic Bounds for Some Common Functions

Exponentials.
For all \( r > 1 \) and all \( d > 0 \),
\( n^d = O(r^n) \).

\( 1.01^n \quad n^{100} \)
Polynomial time

**P:** Running time is $O(n^d)$ for some constant $d$ independent of the input size $n$.

*Nice scaling property:* there is a constant $c$ s.t. *doubling* $n$, time increases only by a factor of $c$.

(E.g., $c \sim 2^d$)

Contrast with exponential: For any constant $c$, there is a $d$ such that $n \rightarrow n+d$ increases time by a factor of more than $c$.

(E.g., $2^n$ vs $2^{n+1}$)
Polynomial time

P: Running time is $O(n^d)$ for some constant $d$ independent of the input size $n$.

Behaves well under composition: if algorithm has a polynomial running time with polynomial number of calls to a subroutine that has polynomial running time, then overall running time is still polynomial.
polynomial vs exponential growth

$2^{2n}$

$2^{n/10}$

$1000n^2$
Why It Matters

Table 2.1 The running times (rounded up) of different algorithms on inputs of increasing size, for a processor performing a million high-level instructions per second. In cases where the running time exceeds $10^{25}$ years, we simply record the algorithm as taking a very long time.

<table>
<thead>
<tr>
<th>$n$</th>
<th>$n$</th>
<th>$n \log_2 n$</th>
<th>$n^2$</th>
<th>$n^3$</th>
<th>$1.5^n$</th>
<th>$2^n$</th>
<th>$n!$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$n = 10$</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>4 sec</td>
</tr>
<tr>
<td>$n = 30$</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>18 min</td>
<td>$10^{25}$ years</td>
</tr>
<tr>
<td>$n = 50$</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>11 min</td>
<td>36 years</td>
<td>very long</td>
</tr>
<tr>
<td>$n = 100$</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>1 sec</td>
<td>12,892 years</td>
<td>$10^{17}$ years</td>
<td>very long</td>
</tr>
<tr>
<td>$n = 1,000$</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>1 sec</td>
<td>18 min</td>
<td>very long</td>
<td>very long</td>
<td>very long</td>
</tr>
<tr>
<td>$n = 10,000$</td>
<td>&lt; 1 sec</td>
<td>&lt; 1 sec</td>
<td>2 min</td>
<td>12 days</td>
<td>very long</td>
<td>very long</td>
<td>very long</td>
</tr>
<tr>
<td>$n = 100,000$</td>
<td>&lt; 1 sec</td>
<td>2 sec</td>
<td>3 hours</td>
<td>32 years</td>
<td>very long</td>
<td>very long</td>
<td>very long</td>
</tr>
<tr>
<td>$n = 1,000,000$</td>
<td>1 sec</td>
<td>20 sec</td>
<td>12 days</td>
<td>31,710 years</td>
<td>very long</td>
<td>very long</td>
<td>very long</td>
</tr>
</tbody>
</table>
Domination

\[ f(n) \text{ is } o(g(n)) \text{ iff } \lim_{n \to \infty} \frac{f(n)}{g(n)} = 0 \]
that is \( g(n) \) dominates \( f(n) \)

If \( a < b \) then \( n^a \) is \( O(n^b) \)

If \( a < b \) then \( n^a \) is \( o(n^b) \)

Note:
if \( f(n) \) is \( \Omega(g(n)) \) then it cannot be \( o(g(n)) \)
Summary

Typical initial goal for algorithm analysis is to find a reasonably tight asymptotic bound on worst case running time as a function of problem size.

This is rarely the last word, but often helps separate good algorithms from blatantly poor ones - so you can concentrate on the good ones!