# Complexity Analysis 2501ICT/7421ICT Nathan 

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## Outline

(1) Measuring Complexity

- Overview
- Measuring the Efficiency of Algorithms
(2) Big-O Notation
- Big-O Analysis
- Common Complexities


## Overview

- Efficiency of Algorithms
- Time and Space
- Measuring Efficiency
- Big-O Analysis
- Examples and Case Studies
- Search Algorithms
- Sort Algorithms


## Why Analyse Complexity?

- Improve Algorithm Efficiency
- need to assess efficiency
$\rightarrow$ can Make a Big Difference
- Large data sets
- Computationally intense problems
- But: Correctness is most important
$\rightarrow$ make correct algorithm efficient, not vice versa!


## Algorithm Efficiency

- Algorithms Consume Resources
- processing time
- memory space
- Compromise
- speed up at expense of memory
- slower, but more memory efficient algorithms
$\rightarrow$ application dependent!


## Problem Size

- Problem Size is the data set size an algorithm works on


## Example (Sum Integers in an Array)

| 12 | 4 | 17 | $\cdots$ | 29 | 18 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 1 | 2 | 3 | $\cdots$ | $n-1$ | $n$ |

- $n$ Integers:
$\rightarrow$ problem size is $n$


## Measuring Efficiency

- Time a program using the computer clock
$\rightarrow$ time command on the command line
- takes too long for large data sets
$\rightarrow$ may not even complete!
- system dependent (compiler, hardware, ...)
- Count block or instruction iterations
- better overall indicator
- works with abstract representations
$\rightarrow$ constant and variable figures (loops)


## Execution Time

- AAAA: Abstractly assess an algorithm
$\rightarrow$ without executing an actual program

```
Example (How many times is S S executed?)
```

```
for (i = 0; i < 10; i++)
```

for (i = 0; i < 10; i++)
for (i = 0; i < N; i++)
for (i = 0; i < N; i++)
Si;

```
    Si;
```

- $S_{1}$ is the Privileged Instruction
- if $S_{1}$ takes a constant amount of time $k_{1}$, how long will the loop take to execute?
$\Rightarrow$ execution time $t=N \cdot k_{1}$


## Execution Time (2)

## Example (Adding a constant Overhead)

$S_{0}$;
for (i = 0; i < N; i++)
$S_{1} ;$
$S_{2}$;

- Assuming $S_{0}$ and $S_{2}$ together take a constant time $k_{2}$ :
$\Rightarrow$ total execution time $t=N \cdot k_{1}+k_{2}$


## Complexity and Problem Size

- Small $n$
- time differences are small
- most algorithms perform similarly
- Large $n$
- huge difference
$\rightarrow$ several seconds vs. thousands of years or more!
- Complexity figure is significant for large values of $n$


## Large Values of n

## Example (comparing different efficiencies)

| $n$ | $n \log _{10} n$ | $n^{2}$ | $2^{n}$ |
| ---: | ---: | ---: | ---: |
| 5 | 3.49 | 25 | 32 |
| 10 | 10 | 100 | 1,024 |
| 100 | 200 | 10,000 | $10^{30}$ |
| 1,000 | 3,000 | $1,000,000$ | $10^{301}$ |
| 10,000 | 40,000 | $100,000,000$ | $10^{3010}$ |

## Influence of Lesser Terms

## Example (Lesser Terms become Insignificant)

| $n$ | $n^{2}$ | $n^{2}+14 n+26$ | Influence |
| ---: | ---: | ---: | ---: |
| 10 | 100 | 266 | $166 \%$ |
| 100 | 10,000 | 11,426 | $14.3 \%$ |
| 1,000 | $1,000,000$ | $1,014,026$ | $1.4 \%$ |
| 10,000 | $100,000,000$ | $100,140,026$ | $0.14 \%$ |

- $n^{2}$ has the biggest effect
$\Rightarrow$ lesser terms become insignificant!


## Big-O Notation

- Less Significant Terms are Ignored
$\Rightarrow n^{2}+14 n+26$ becomes $\mathrm{O}\left(n^{2}\right)$
$\rightarrow \mathrm{O}\left(n^{2}\right)$ is read "Order n Squared"
- General Case
- factor with highest significance determines Order of Magnitude
$\rightarrow \mathrm{O}\left(n^{k}\right): a+b n+c n^{2}+\cdots+n^{k}$
$\rightarrow \mathrm{O}\left(k^{n}\right): a+b n+c n^{2}+\cdots+n^{k}+k^{n}$


## Magnitude of Complexity

Example (most significant term matters)

$$
\begin{array}{ll}
2 n^{2}+6 & =\mathrm{O}\left(n^{2}\right) \\
n^{3}+3000 n^{2}+6 & =\mathrm{O}\left(n^{3}\right) \\
2^{n}+4 n^{1} 00+5 n & =\mathrm{O}\left(2^{n}\right)
\end{array}
$$

- Placement of data may influence algorithm complexity
- Best-Case, Average, and Worst-Case
$\rightarrow$ Significant: Average and Worst-Case


## Big-O Limitations

- Less Significant Terms
$\rightarrow$ can be quite significant for small and medium size data sets!
- Constant of Proportionality
$\rightarrow 800 n^{2}$
- almost 3 orders of magnitude more complex than $n^{2}$


## Common Orders of Magnitude

## O(1) Constant <br> O(log $n) \quad$ Logarithmic <br> $\mathrm{O}(n) \quad$ Linear <br> $O(n \log n)$ Log Linear <br> $\mathrm{O}\left(n^{2}\right) \quad n$-Squared <br> $\mathrm{O}\left(2^{n}\right) \quad$ Exponential

Example (Common Orders of Magnitude)

## Common Cases

- Single loop processing $n$ items
- O(n)
- Two nested loops of $n$ items
- $\mathrm{O}\left(n^{2}\right)$
- Binary Search
- $\mathrm{O}\left(\log _{2} n\right)$
- Efficient Sort
- $\mathrm{O}\left(n \log _{2} n\right)$


## Logarithms

- $\log _{2} n$ complexity is very common!
$\rightarrow \log n$
- Examples:
- Repeated doubling
- Start at 1, double until size reaches $n$
- Repeated halving
- Start at $n$, half data set until 1 is reached
- Binary searches, efficient sorting, ...

