

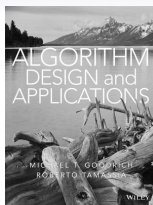
COMP26120: Algorithms and Imperative Programming


Lecture 6: Introducing Complexity

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- You need this book:
- 
- The image shows the front cover of the textbook 'Algorithms and Applications' by Michael T. Goodrich and Roberto Tamassia. The cover features a grayscale photograph of a person's face, possibly a child, looking upwards. The title 'APPLICATIONS' is at the top in large, white, sans-serif capital letters. Below it, the authors' names 'MICHAEL T. GOODRICH' and 'ROBERTO TAMASSIA' are printed in smaller white capital letters. The Wiley logo is in the bottom right corner.
- Make sure you use the up-to-date edition. It is available on the course materials page:
<http://studentnet.cs.manchester.ac.uk/ugt/2015/COMP26120/syllabus/>
 - Read Ch. 1 (pp. 1–50).
 - Pay particular attention to:
 - Pseudocode
 - Big-O notation and its relatives
 - The mathematical basics.
 - Also read pp. 689–690 and 695–696.

Outline

Getting started: two ways of computing variance

Big-O notation

Some details: What is an operation, and how big is a number?

Example: powers in modular arithmetic

Euclid's algorithm for finding highest common factors

- Let us begin with a simple example.
- Suppose we have a collection of numbers x_1, \dots, x_n , and want to compute the *variance*, defined by the formula:

$$\sigma^2 = \frac{1}{n^2} \sum_{i=1}^{n-1} \sum_{j=i+1}^n (x_i - x_j)^2 = \frac{1}{2n^2} \sum_{i=1}^n \sum_{j=1}^n (x_i - x_j)^2.$$

- We could just do it:

```

var1( $x_1, \dots, x_n$ )
   $s := 0$ 
  for  $i$  from 1 to  $n - 1$ 
    for  $j$  from  $i + 1$  to  $n$ 
       $s := s + (x_i - x_j)^2$ 
  return  $s/n^2$ 
end

```

- To see why this wouldn't be a good idea, let's count how much work is done.

```
var1( $x_1, \dots, x_n$ )  
   $s := 0$   
  for  $i$  from 1 to  $n - 1$   
    for  $j$  from  $i + 1$  to  $n$   
       $s := s + (x_i - x_j)^2$   
  return  $s/n^2$   
end
```

- We do $\sum_{i=1}^{n-1} (n - i) = \sum_{i=1}^{n-1} i = \frac{1}{2}(n - 1)n$ executions of the line $s := s + (x_i - x_j)^2$ plus one final squaring and division—about $\frac{3}{2}(n - 1)n + 2$ operations.

- But suppose you notice that the variance of x_1, \dots, x_n is actually the mean squared distance from the mean, μ . Noting that $\mu = \sum_{i=1}^n x_i / n$:

$$\sigma^2 = \sum_{i=1}^{n-1} \sum_{j=i+1}^n (x_i - x_j)^2 / n^2 = \sum_{i=1}^n (x_i - \mu)^2 / n.$$

Then the following algorithm will then work:

```
var2( $x_1, \dots, x_n$ )  
   $m := 0$   
  for  $i$  from 1 to  $n$   
     $m := m + x_i$   
   $m := m/n$  %  $m$  now holds the mean  
   $s := 0$   
  for  $i$  from 1 to  $n$   
     $s := s + (x_i - m)^2$   
  return  $s/n$   
end
```

- Now let's see how much work was done again:

```
var2( $x_1, \dots, x_n$ )  
   $m := 0$   
  for  $i$  from 1 to  $n$   
     $m := m + x_i$   
   $m := m/n$  %  $m$  now holds the mean  
   $s := 0$   
  for  $i$  from 1 to  $n$   
     $s := s + (x_i - m)^2$   
  return  $s/n$   
end
```

- Here we do n additions in the first loop, and n subtractions, squarings and additions in the second loop, plus one division after each loop, making $4n + 2$ operations, much less (for large n) than $\frac{3}{2}(n - 1)n + 2$.

- Observe
 - Algorithms are given in [pseudocode](#).
 - The [correctness](#) of the algorithm `var2` needs to be established. Specifically, we have to prove that

$$\frac{1}{n^2} \sum_{i=1}^{n-1} \sum_{j=i+1}^n (x_i - x_j)^2 = \frac{1}{n} \sum_{i=1}^n \left(x_i - \frac{1}{n} \sum_{j=1}^n x_j \right)^2.$$

- We could quibble endlessly about *exactly* how many operations are involved in these algorithms, but we'd rather not ...
 - Such quibbles are irrelevant, because `var2` is clearly superior to `var1`.
- This lecture is about how to articulate these ideas.

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- When comparing growth-rates of functions, it is often useful to ignore
 - small values
 - linear factors
- That is, we are interested in how functions behave in the long run, and up to a linear factor.
- This is essentially to enable us to abstract away from relatively trivial implementation details.

- The main device used for this is big-O notation. If $f : \mathbb{N} \rightarrow \mathbb{N}$ is a function, then $O(f)$ denotes the set of functions:

$$\{g : \mathbb{N} \rightarrow \mathbb{N} \mid \exists n_0 \in \mathbb{N} \text{ and } c \in \mathbb{R}^+ \text{ s.t. } \forall n > n_0, g(n) \leq c \cdot f(n)\}.$$

- Thus, $O(f)$ denotes a *set* of functions.

- To see why this is useful, consider the sets of functions

$$O(n) = \{g : \mathbb{N} \rightarrow \mathbb{N} \mid \exists n_0 \in \mathbb{N}, c \in \mathbb{R}^+ \text{ s.t. } \forall n > n_0, g(n) \leq cn\}$$

$$O(n^2) = \{g : \mathbb{N} \rightarrow \mathbb{N} \mid \exists n_0 \in \mathbb{N}, c \in \mathbb{R}^+ \text{ s.t. } \forall n > n_0, g(n) \leq cn^2\}.$$

- The following should now be obvious:
 - The function $g_2(n) = 4n + 2$ is in $O(n)$.
 - The function $g_1(n) = \frac{3}{2}(n-1)n + 2$ is in $O(n^2)$.
 - The function $g_1(n)$ is not in $O(n)$.
- Notice, of course, that $O(n) \subsetneq O(n^2)$.

- So now we can express succinctly the difference between running times of our algorithms `var1` and `var2`:
 - The running time of `var1` is in $O(n^2)$ (but not in $O(n)$);
 - The running time of `var2` is in $O(n)$.
- Often, we forget that $O(f)$ is technically a set of functions, and say:
 - The running time of `var1` is $O(n^2)$ (or: is order n^2);
 - The running time of `var2` is $O(n)$ (or: is order n).

But this is really just a manner of speaking.

- Of course, you can have $O(f)$ for any $f : \mathbb{N} \rightarrow \mathbb{N}$:
 - $O(\log n)$
 - $O(\log^2 n)$
 - $O(\sqrt{n})$
 - $O(n), O(n^2), O(n^3), \dots$
 - $O(2^n), O(2^{n^2}), \dots$
 - $O(2^{2^n}), O(2^{2^{2^n}}), \dots$

- To think about:
 - Make sure you understand why $f(n) \leq g(n)$ for all n implies $O(f) \subseteq O(g)$.
 - Why do you not hear people talking about $O(6n + 7)$?
 - Give a succinct but accurate characterization of $O(1)$ in plain English.

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- We said that the time-complexity of `var2` is in $O(n)$, but what, exactly, does this mean?
- Answer: to say that an algorithm A runs in time g means the following.

Given an input of size n , the number of operations executed by A is bounded above by $g(n)$.

- This raises two important issues:
 - What is an operation?
 - How do we measure the size of the input?

- Deciding what to count as an operation is a bit of a black art. It depends on what you want your analysis for.
- For most practical applications, it is okay to take the following as operations:
 - arithmetic operations (e.g. $+$, $*$, $/$, $\%$) on all the basic number types)
 - assignments (e.g. $a := b$, $a[i] = t$, $t = a[i]$)
 - basic tests (e.g. $a = b$, $a \geq b$)
 - Boolean operations (e.g. $\&$, $!$, $||$).
- Things like allocating memory, managing loops are often ignored—again, this may depend on the application.

- Note that, for some applications, this accounting régime might be misleading.
- Imagine, for example, an cryptographic algorithm requiring to perform arithmetic on numbers hundreds of digits long.
- In this case, we would probably want to count the number of logical operations involved.
- For example, to multiply numbers with p bits and q bits, we require in general about pq logical operations.
- There is a formal model of computation, the [Turing Machine](#), which specifies precisely what counts as a basic operation.
- But in this course, we shall not use the Turing machine model.

- The question of how to measure the size of the input is rather trickier.
- Officially, the input to an algorithm is a [string](#).
- Often, that string represents a number, or a sequence of numbers, but it is still a string.
- What is the size of the following inputs?
 - The cat sat on the mat
 - 1
 - 13
 - 445
 - 65535
- The size of a positive integer n (in canonical decimal representation) is $\lfloor \log_{10} n \rfloor + 1$, [not](#): n .

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- Recall the definition of $m \bmod k$, for k an integer greater than 1:

$$17 \bmod 6 = 5$$

$$14 \bmod 2 = 0$$

$$117 \bmod 10 = 7$$

- When performing arithmetic mod k , we can stay within the numbers $0, \dots, k - 1$:

$$17 + 5564 \bmod 10 = 7 + 4 \bmod 10 = 11 \bmod 10 = 1$$

$$17 \cdot 5564 \bmod 10 = 7 \cdot 4 \bmod 10 = 28 \bmod 10 = 8$$

$$5564^{17} \bmod 10 = 4^{17} \bmod 10 = 17179869184 \bmod 10 = 4$$

- Modular arithmetic is important in cryptography.

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- Modular arithmetic is particularly nice when the modulus is a prime number, p .
- If $1 \leq a < p$, then there is a unique number b such that

$$a \cdot b = b \cdot a = 1 \pmod{p}.$$

In that case we call b the **inverse** of a (modulo p) and write $b = a^{-1}$.

- For example,

$$3 \cdot 5 = 5 \cdot 3 = 1 \pmod{7},$$

so 3 and 5 are inverses modulo 7.

- Here is an algorithm to compute $a^b \bmod k$.
(Note that we may as well assume that $a < k$.)

```
pow1(a, b, k)
  s := 1
  for i from 1 to b
    s := s · a mod k
  return s
end
```

- The number of operations performed here is clearly $O(b)$.
- Therefore the time complexity is ...

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- The number of operations performed here is clearly $O(b)$.
- Therefore the time complexity is $O(2^n)$ —i.e. [exponential](#).
- That's right, exponential, not linear: the size of the input b is $\log b$. (Note that a and k don't really matter here.)
- Reminder: $2^{\log_2 n} = n$.

- Here is a better algorithm to compute $a^b \bmod k$.

```
pow2(a, b, k)
  d := a, e := b, s := 1
  until e = 0
    if e is odd
      s := s · d mod k
    d := d2 mod k
    e := ⌊e/2⌋
  return s
end
```

- The number of operations performed here is proportional to the number of times $d = b$ can be halved before reaching 0, i.e. at most $\lceil \log_2 b \rceil$. Thus, this algorithm has running time in $O(n)$, i.e. **linear** in the size n of the input b . (Again, a and k don't really matter here.)

- To see how this number works, think of b in terms of its binary representation $b = b_{n-1}, \dots, b_0$, i.e.

$$b = \sum_{h=0}^{n-1} b_h \cdot 2^h,$$

so that

$$a^b = \prod_{h=0}^{n-1} a^{(b_h \cdot 2^h)}$$

And of course

$$a^{(b_h \cdot 2^h)} = \begin{cases} 1 & \text{if } b_h = 0 \\ a^{(2^h)} & \text{if } b_h = 1. \end{cases}$$

But the variable e holds a^{2^h} on entry to the h th iteration on the loop (counting from $h = 0$ to $h = n - 1$).

- Compute $7^{11} \bmod 10$. (N.B. 7^{11} is actually 1977326743.)

pow2(a, b, k)

$d := a, e := b, s := 1$

until $e = 0$

if e is odd

$s := s \cdot d \bmod k$

$d := d^2 \bmod k$

$e := \lfloor e/2 \rfloor$

return s

end

Before loop:

$s \leftarrow 1$

$d \leftarrow 7$

$e \leftarrow 11$ (= Binary 1011)

Round 1:

$s \leftarrow 7$ (e is odd and $1 \cdot 7 = 7 \bmod 10$)

$d \leftarrow 9$ ($7^2 = 9 \bmod 10$)

$e \leftarrow 5$

Round 2:

$s \leftarrow 3$ (e is odd and $7 \cdot 9 = 3 \bmod 10$)

$d \leftarrow 1$ ($7^4 = 9^2 = 1 \bmod 10$)

$e \leftarrow 2$

Round 3:

$s \leftarrow 3$ (e is even)

$d \leftarrow 1$ ($7^8 = 1^2 = 1 \bmod 10$)

$e \leftarrow 1$

Round 4:

$s \leftarrow 3$ (e is odd and $3 \cdot 1 = 1 \bmod 10$)

$d \leftarrow 1$ ($7^{16} = 1^2 = 1 \bmod 10$)

$e \leftarrow 0$

- At some point d became 1. Do you see an optimization?

- Raising positive numbers to various powers modulo k produces 1 more often than you think.
- This is of special interest when k is some prime number, p .
- For example, set $k = p = 7$. In the following, all calculations are performed modulo 7.

$$1^1 = 1$$

$$2^1 = 2 \quad 2^2 = 4 \quad 2^3 = 1$$

$$3^1 = 3 \quad 3^2 = 2 \quad 3^3 = 6 \quad 3^4 = 4 \quad 3^5 = 5 \quad 3^6 = 1$$

$$4^1 = 4 \quad 4^2 = 2 \quad 4^3 = 1$$

$$5^1 = 5 \quad 5^2 = 4 \quad 5^3 = 6 \quad 5^4 = 2 \quad 5^5 = 3 \quad 5^6 = 1$$

- Notice that, for $1 \leq a < p$, the smallest k such that $a^k = 1 \pmod p$ divides $p - 1$ (this is always true for p prime).
- Hence a^{p-1} is always 1 (this is [Fermat's little theorem](#)).
- However, there is always some number a such that the various powers g^i cover the whole of $\{1, 2, \dots, p - 1\}$ (g is a [primitive root](#) modulo p).

- Let p be a prime, and consider the equation

$$a^x = y \pmod{p}.$$

- If a is a primitive root modulo p , then, for every y ($1 \leq y < p$), such an x ($1 \leq x < p$) exists.
- In that case, the number x is called the **discrete logarithm** of y with base a , modulo p .
- Thus, the discrete logarithm is an inverse of exponentiation.
- We have seen that, for fixed a and p , computing

$$y = a^x \pmod{p}$$

for a given x is very fast. However, no such fast algorithm is known for recovering x from y .

- That is: modular exponentiation may be an example of a **one-way** function—easy to compute, hard to invert.

- Such one-way functions can be used for cryptography.
- Fix a prime, p a primitive root g modulo p .
- Choose a **private key**: x ($1 \leq x < p - 1$).
- Broadcast the **public key**: (p, g, y) , where $y = g^x$.
- Suppose someone wants to send you a message M (assume M is an integer $1 \leq M < p$).
- He picks k relatively prime to $p - 1$, sets

$$a \leftarrow g^k \mod p$$

$$b \rightarrow My^k \mod p$$

and sends the ciphertext $C = (a, b)$.

- To decode $C = (a, b)$, you set

$$M' \leftarrow b/(a^x) \mod p.$$

- To see that you get the proper message:

$$\begin{aligned}M' &= b/(a^x) \mod p = My^k(a^x)^{-1} \mod p \\&= M(g^{xk})(g^{xk})^{-1} \mod p \\&= M\end{aligned}$$

- To see that this is secure, notice that to encode, one needs the public key $y = g^x$, but to decode, one needs the private key x (which only you have).
- In other words, to break the code, an enemy needs to be able to find the discrete logarithm of y to the base g , modulo p .
- The existence of one-way functions is equivalent to the conjecture $P \neq NP$.

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Euclid's algorithm for finding highest common factors

- Suppose you want to compute the highest common factor (hcf) of two non-negative integers a and b .
- Note that the hcf is sometimes called the *greatest common divisor* (*gcd*).
- Assume $a \geq b$. A little thought shows that, letting $r = a \bmod b$, we have, for some q

$$a = qb + r$$

$$r = a - qb$$

so that the common factors of a and b are the same as the common factors of b and r . Hence:

$$\text{hcf}(a, b) = \text{hcf}(b, r).$$

- This gives us the following very elegant algorithm for computing highest common factors.

```
hcf( $a, b$ )      (Assume  $0 \neq a \geq b$ )  
  if  $b = 0$   
    return  $a$   
  else  
     $r := a \bmod b$   
    return hcf( $b, r$ )  
end
```

- This is so simple, it hurts.

- How long does $\text{hcf}(a, b)$ take to run?

Well, let a_1, a_2, \dots, a_ℓ be the first arguments of successive calls to hcf in the computation of $\text{hcf}(a, b)$. (Thus, $a = a_1$.)

Certainly $a_1 > a_2 > \dots > a_\ell$, so the algorithm definitely terminates.

Assuming $\ell > 2$, consider h in the range $1 \leq h \leq \ell - 2$. If $a_{h+1} \leq a_h/2$, then $a_{h+2} < a_h/2$. On the other hand, if $a_{h+1} > a_h/2$, then $a_{h+2} = a_h \bmod a_{h+1} < a_h/2$.

Either way, $a_{h+2} < a_h/2$. So the number of iterations is at most $\max(2, 2\lceil \log_2 a \rceil)$. That is, the algorithm is linear in the size of the input. (Actually, the algorithm performs slightly better than this.)