



# ALGORITHMS & DATA STRUCTURES

SET08 | 22

## **LECTURE 02:**

# ***ALGORITHMS & COMPLEXITY*** *(& MAYBE A LITTLE COMPUTABILITY)*

Dr Simon Wells

[s.wells@napier.ac.uk](mailto:s.wells@napier.ac.uk)

<http://www.simonwells.org>

# TL/DR

- Not every problem is solvable using a computer. Computer Science is all about working out what the characteristics and performance of problems that are (not) solvable by computers.



## **At the end of this lecture you will be able to:**

- Inspect code & roughly determine the order of complexity of its computations
- Describe the features & function of the Turing Machine
- Understand some of the limits of computation

# OVERVIEW

- Algorithms
- An introduction to complexity (time & space)
- Some practical methods for determining complexity
- A tiny digression into computability



# ALGORITHMS? WHAT ARE THEY? WHAT ARE THEY FOR?



“  
A LIST OF INSTRUCTIONS  
THAT CAN BE FOLLOWED TO  
SOLVE A PROBLEM.  
”

# ALGORITHMS

- This is one of those areas where there is overlap between computers, computer science, and mathematics
- An *unambiguous* specification of how to solve a (class of) problems
- We have algorithms for
  - Calculating results
  - Data processing

*(two ways of using algorithms that we're used to)*

- But also *Artificial Intelligence* - uses algorithms (Path-finding, Machine Learning, Neural Nets)

# ALGORITHMS

- An effective method expressed within a finite amount of space & time using a well-defined formal language for calculating a function
- Start in an initial state (with an input [might be none])
- Instructions describe a computation
- When executed there are a finite number of well-defined successive states that eventually produce an *output* and the computation terminates at a final ending state
- NB. Transitions between states need not be deterministic
  - If you're interested take a look at **Bloom Filters** which incorporate a degree of randomness within the algorithm - It's a *probabilistic* data structure. Useful if amount of data requires an impractical amount of memory





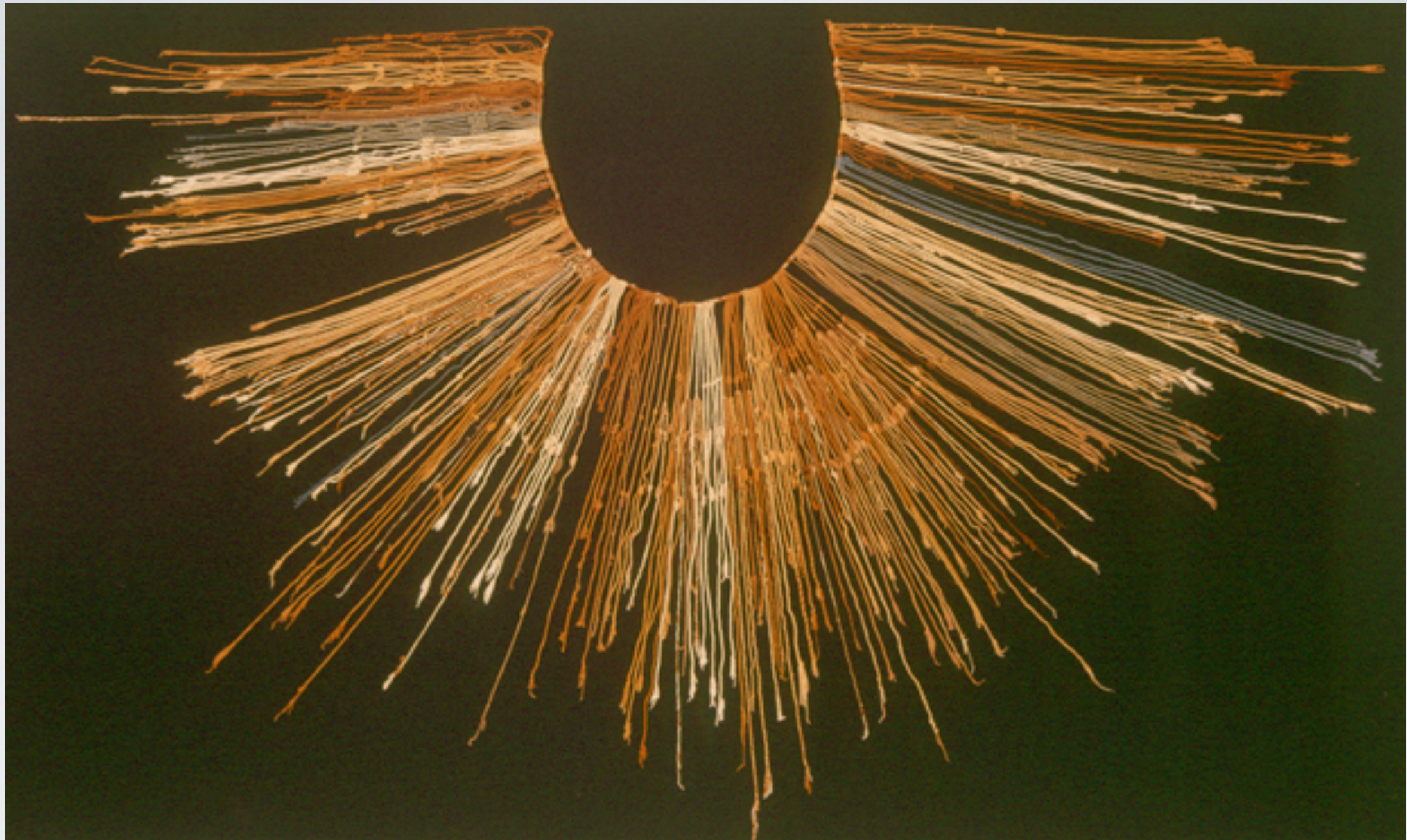
# EFFECTIVE METHODS

- Finite number of exact finite instructions
- When applied to a problem from its class:
  - It always terminates after a finite number of steps
  - It always produces a correct answer
- Note: This is getting us to the edge of hard computer science questions like “what is computable?”
- *In principle, a person could do the work by hand...*
  - *only need to follow the algorithm rigorously*

# HISTORY

- Still some discussion of formal definition of *algorithm* and what it means to be computable
  - Concept been around for centuries (at least back to Euclid)
  - Hilbert (1928) Entscheidungsproblem (decision problem)
  - Logicians refined the problems, e.g. Godel, Herbrand, Kleene ('30s)
  - Alonzo Church (1936) Lambda Calculus
  - Alan Turing Turning





# QUIPUS

Recording information with knotted ropes





QUIPUS CAN GET QUITE BIG



# CLASSIFYING ALGORITHMS





# BIG OH NOTATION

- Big Oh is just fancy sounding words for insight & practices that many professional developers know & use (often without realising it)
- Big Oh refers to the “order” associated with the performance, i.e. the degree of complexity , so  $O(n)$  is read “The order of  $n$ ”
- $O$  really refers to the Order function
- A function’s Big Oh notation is generally determined by how it responds to different inputs
  - e.g. How much slower is this function if we give it 1,000,000 items instead of 1 item?
- Essentially we are *approximating* orders of magnitude
  - i.e. Does the algorithm run in constant time, linear time, quadratic time, logarithmic time?
- This lets us predict how a given algorithm will perform for a given input size



# OTHER NOTATIONS

- Big  $O$  gives the upper bound
- Big  $\Omega$  (Omega) gives the lower bound
- There is Big  $\Theta$  (Theta) notation to asymptotically bound the growth to within constant factors above and below
- Important because a single notation doesn't always give the full story
- Each notation can also be used to reason about best, worst, & average cases



# CALCULATING #1

- We take measurements of how an algorithm performs
- Graph the results (where  $n$  the number of items corresponds to the x axis)
- Match the curve to known performance curves
- Dealing with worst case scenarios (Can chart the upper & lower bounds which yields a )
- We graph the  $n$  in  $O(n)$  where  $n$  corresponds to x axis



# CALCULATING #2

```
def count_ones(a_list):
```

```
    total = 0
```

```
    for element in a_list:
```

```
        if element == 1:
```

```
            total += 1
```

```
    return total
```

Constant time  $O(1)$

Linear time  $O(n)$

Constant time  $O(1)$

Constant time  $O(1)$

- By counting/inspecting operations:

$O(2n)$  isn't much different to  $O(n)$

$$O(1) + O(n) * (O(1) + O(1))$$

Reduces to  $O(2n) + O(1)$

Only care about biggest terms

**Count operations,  
simplify, drop  
multipliers**



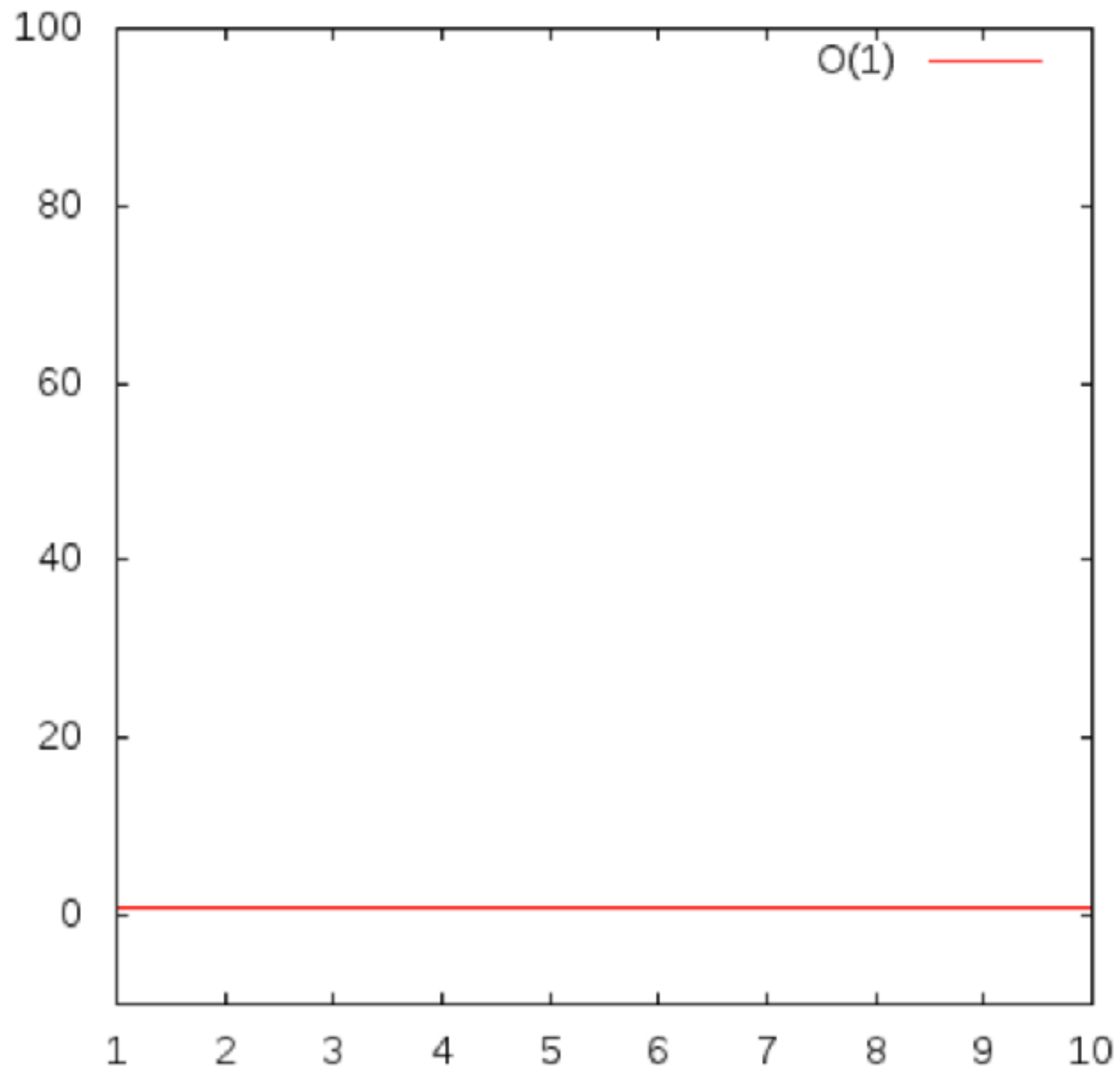
# CONSTANT TIME

- An algorithm runs in constant time if it requires the same amount of time regardless of input size
- Big Oh Notation/Complexity is  $O(1)$
- No matter how big the input will always take the same amount of time
- Example: Access any element of an array, push & pop to a fixed size stack, Enqueue to & dequeue from a fixed size queue

```
def is_none(item):  
    return item is None
```



$O(1)$  runtime



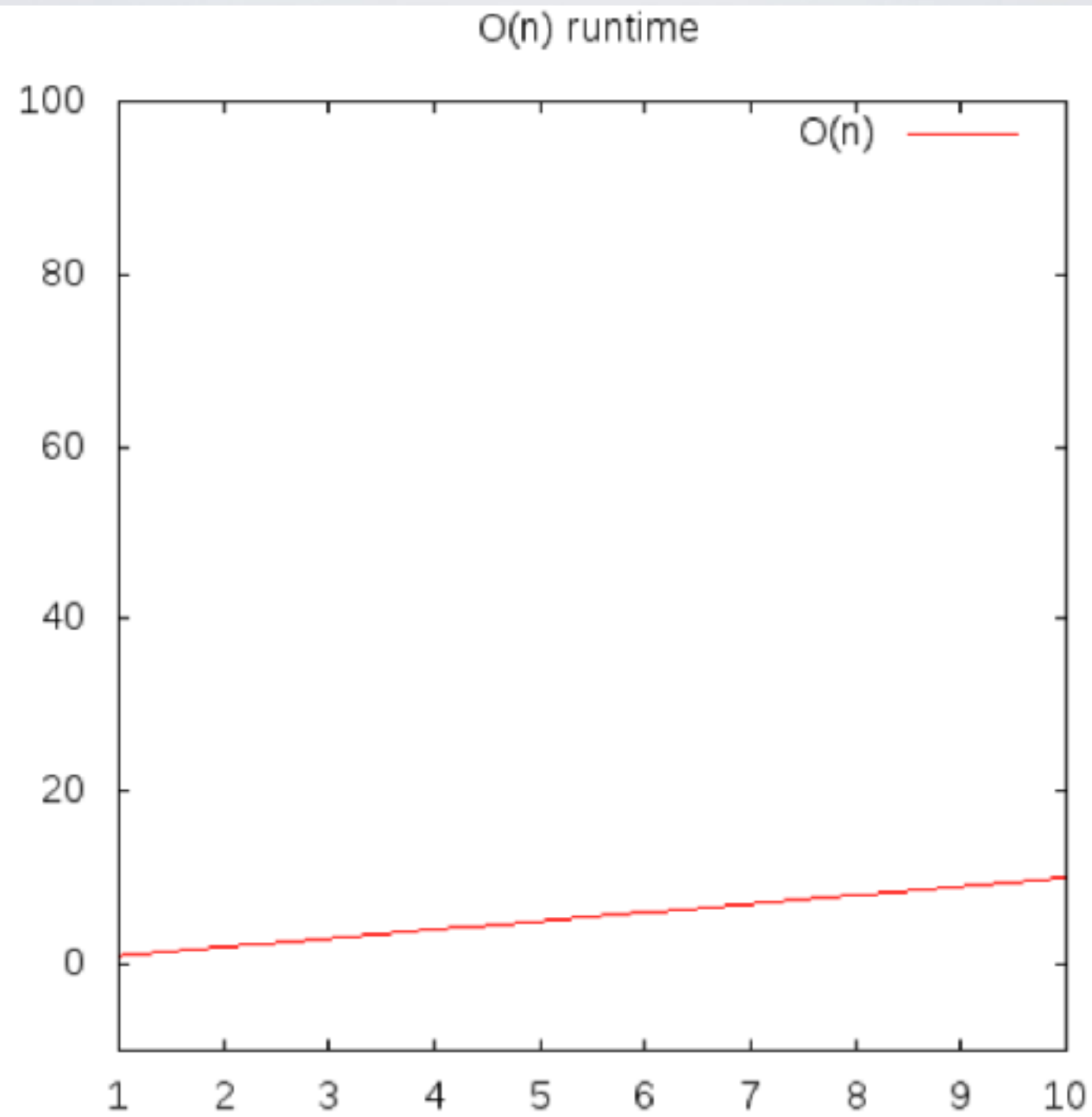
# LINEAR TIME

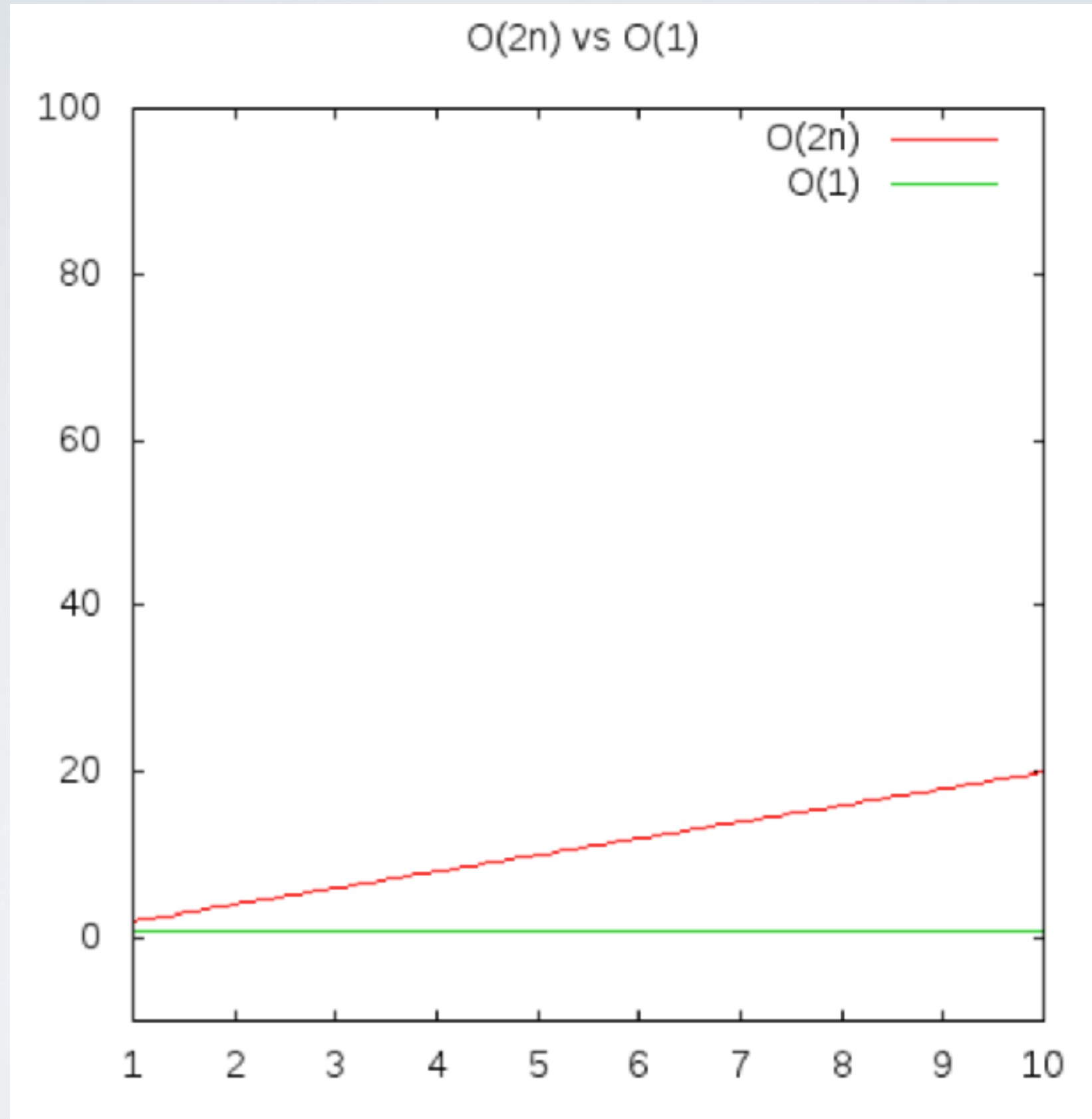
- An algorithm runs in linear time if the time it takes to execute is directly proportional to input size
- Complexity is  **$O(n)$**
- **Examples:**
  - **Array:** Linear search, Traversal, Find minimum
  - **ArrayList:** Contains
  - **Queue:** Contains

# LINEAR TIME

- Call with, e.g. **item\_in\_list(2, [1,2,3])**
- If we graph the time it takes the function with different sized inputs (arrays) we'd see that this approximately corresponds to the number of items in the array

```
def item_in_list(to_check, the_list):  
    for item in the_list:  
        if to_check == item:  
            return True  
    return False
```



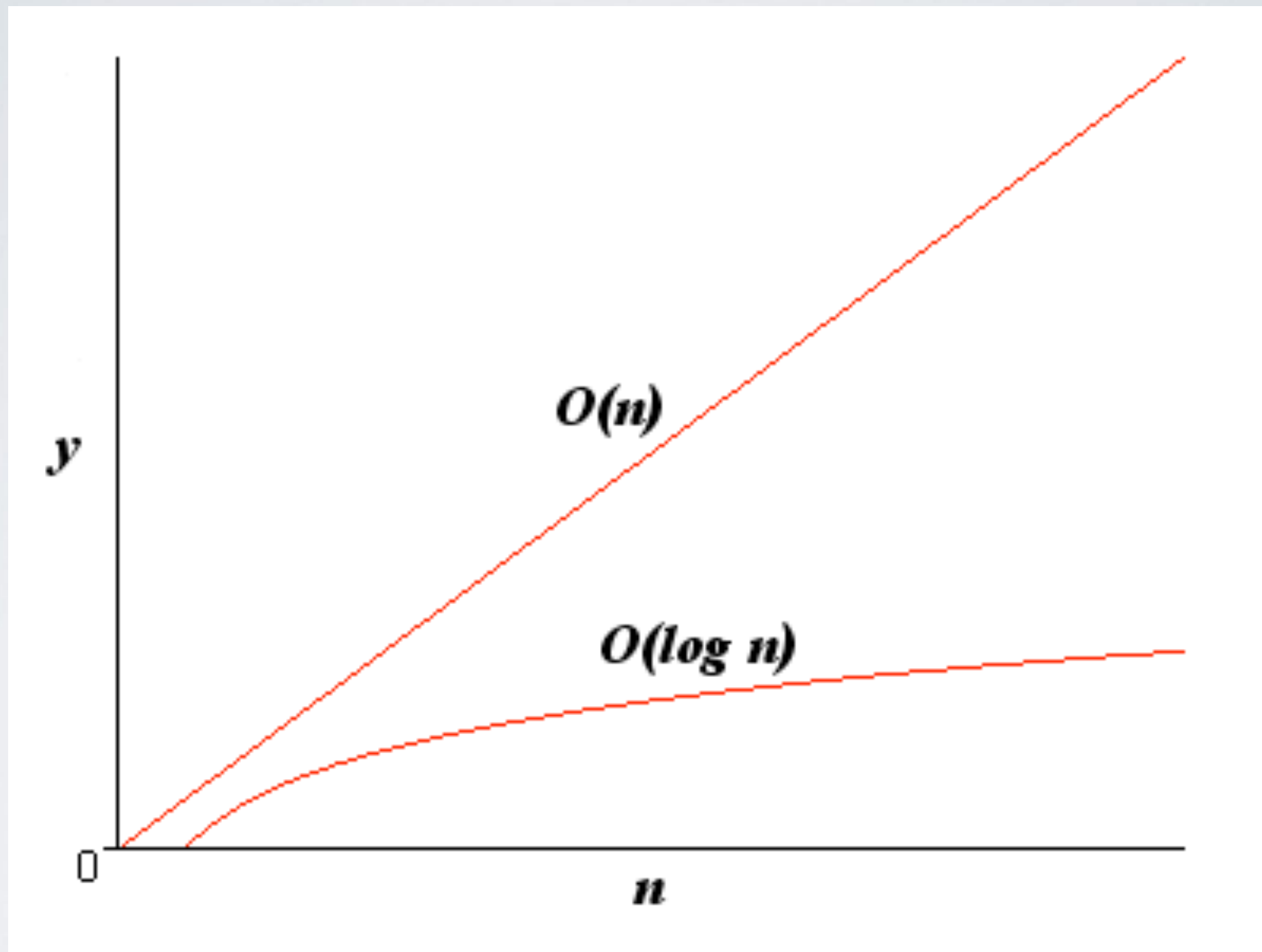




# LOGARITHMIC TIME

- If the execution time is proportional to the logarithm of the input size
- A common attribute of algorithms with logarithmic running times is that there is often a choice of new element on which to perform an action & only one needs to be chosen
- Example: Binary Search
- Classical “divide & conquer” scenarios, e.g. looking up someone in the phonebook

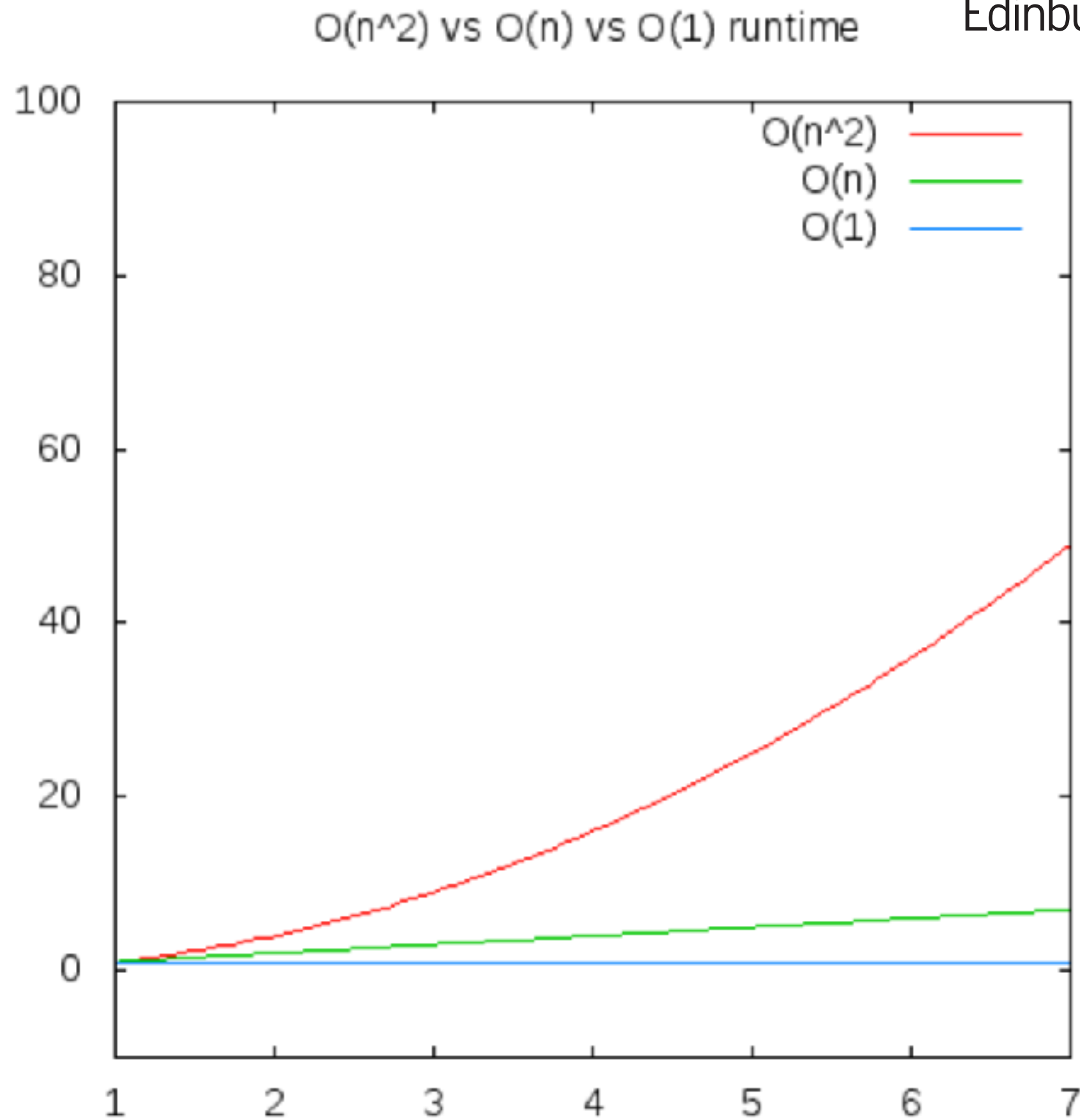




# QUADRATIC TIME

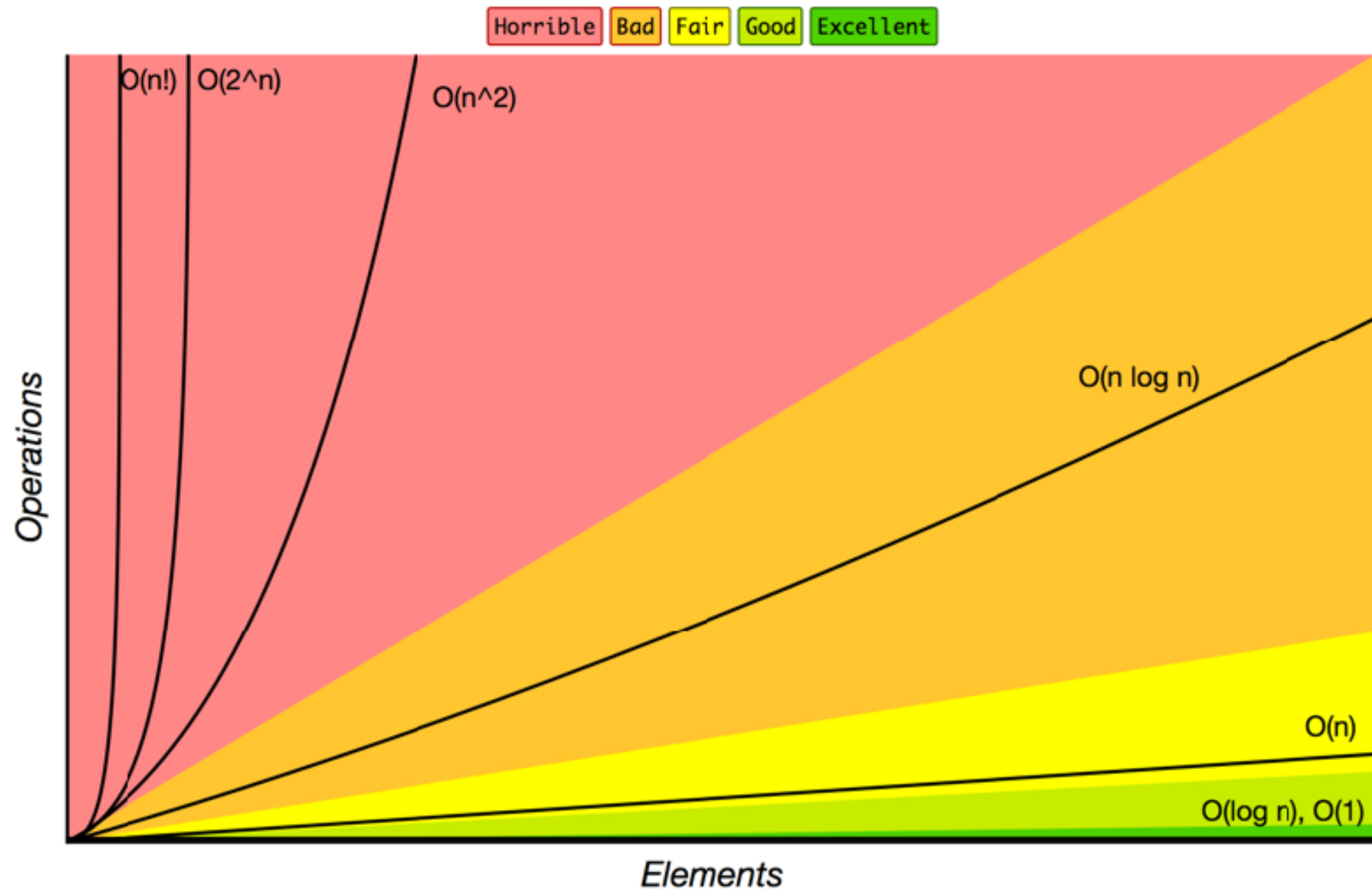
- An algorithm runs in quadratic time if its execution time is proportional to the square of the input size
- For every item,  $n$ , in the list we have to do  $n$  operations
- $n * n == n^2$ , i.e.  $O(n^2)$
- Example: Bubble, Selection, & Insertion sorts
- Given a list, e.g.  $[1,2,3]$  get back all combinations:
  - $[(1,1) (1,2), (1,3), (2, 1), (2, 2), (2, 3), (3, 1), (3, 2), (3, 3)]$

```
def all_combinations(the_list):
    results = []
    for item in the_list:
        for inner_item in the_list:
            results.append((item, inner_item))
    return results
```





## Big-O Complexity Chart



FROM: [HTTP://BIGOCHEATSHEET.COM/](http://BIGOCHEATSHEET.COM/)



Data Structure	Time Complexity								Space Complexity
	Average				Worst				Worst
	Access	Search	Insertion	Deletion	Access	Search	Insertion	Deletion	
<u>Array</u>	$\theta(1)$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$
<u>Stack</u>	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$
<u>Queue</u>	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$
<u>Singly-Linked List</u>	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$
<u>Doubly-Linked List</u>	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$	$\theta(n)$	$\theta(1)$	$\theta(1)$	$\theta(n)$
<u>Skip List</u>	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n \log(n))$
<u>Hash Table</u>	N/A	$\theta(1)$	$\theta(1)$	$\theta(1)$	N/A	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$
<u>Binary Search Tree</u>	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$
<u>Cartesian Tree</u>	N/A	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	N/A	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$
<u>B-Tree</u>	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$
<u>Red-Black Tree</u>	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$
<u>Splay Tree</u>	N/A	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	N/A	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$
<u>AVL Tree</u>	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$
<u>KD Tree</u>	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(\log(n))$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$	$\theta(n)$

FROM: [HTTP://BIGOCHEATSHEET.COM/](http://BIGOCHEATSHEET.COM/)



# PRACTICAL SKILLS

- Many professional programmers will tell you that they don't use Big O notation and it hasn't been important to the careers.
- Perhaps in the most literal sense they are correct - they haven't specifically said that something has a big O or big Omega or big Theta value, but...
  - ... they do, through experience, develop a sense for how long certain tasks take, how much memory is needed, whether a given problem is tractable on the resources available. &c
- However, ask any programmer how they evaluate & optimise their code they will talk about things like
  - Input size & looping as indicators of where a program will spend time computing
  - Profiling (using tools to determine where your program spends time)

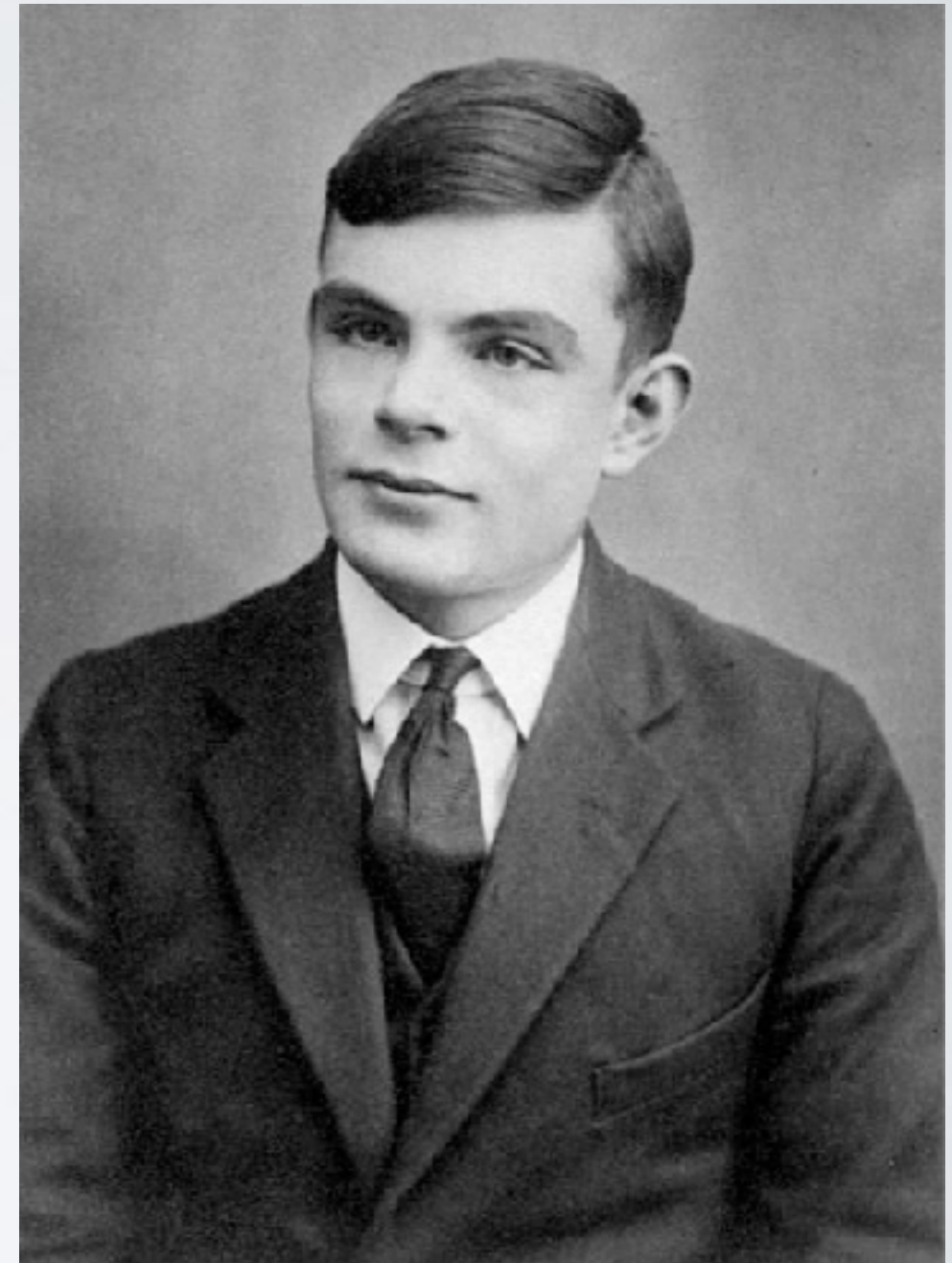


# COMPUTABILITY



# ALAN TURING (1912-54)

- English Computer Scientist (before computers really existed)
- Father of both theoretical Computer Scientist & Artificial Intelligence (also worked in Mathematics, Philosophy & Theoretical Biology)
- Worked for GCHQ during WW2 performing cryptanalysis
- Post WW2 worked on the National Physics Laboratory ACE & the Manchester computers (SSEM, Baby, &c.)
- Replaced Gödel's formal language describing results on the limits of proof & computation with a simple hypothetical device: A formal description of a computational device that became known as a Turing Machine.







# TURING'S WORK

- Started work on the **Halting Problem** (we'll get to that) in 1936
- Proved that you cannot create a program that solves (gives an answer) to the Halting Problem for all possible inputs
- Elements of the proof of this specified a mathematical definition of a computer and program - this became the known as the **Turing Machine**
- Significant because one of the first problems proven to be unsolvable.

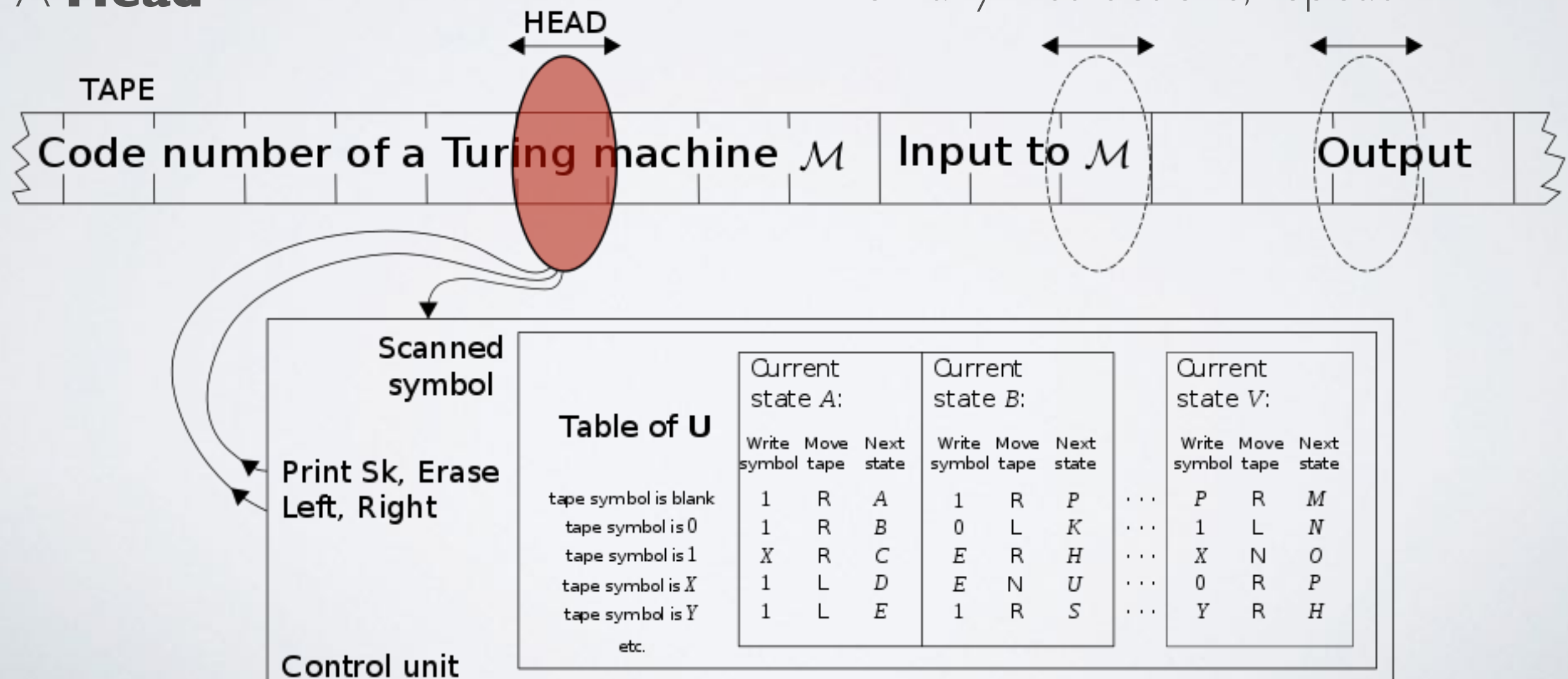
# TURING'S MODEL OF COMPUTATION

- Theoretical mathematical model of computation:
  - **An abstract machine that manipulates symbols on a strip of tape according to a set of rules**
- *Recall we saw another model earlier in the von Neumann architecture*
- Simpler but paradoxically also more powerful
  - e.g. removes practical issues such as bus (& bottleneck)
  - Can simulate any computer algorithm
  - Strictly a **Universal** Turing Machine - A Turing Machine that can take as input a description of another Turing Machine
- von Neumann more than sufficient for most reasoning about data structures & algorithms (close to reality) but Turing necessary to study limits of computation NB. von Neumann very likely influenced by Turing in design or earliest physical computers
- Strictly impossible to implement (we cannot build anything of infinite size)

# TURING MACHINE

- A **Tape** of infinite length (*think of tape is being like memory with each cell laid out next to the other in a long line*)
- A **Head**

- A **State Register**
- A finite **Table of instructions**
- Read tape, decode information, act on any instructions, repeat.





# HALTING PROBLEM

- Determining from a description of an arbitrary program & an input whether the program will finish running or continue forever
- Phrased in terms of Turing machines:
  - Given a description of a Turing machine & initial input, asks whether the program, when executed on the input, will halt (complete) or continue forever.
  - Been shown that not possible to construct a Turing machine that can answer this question
    - e.g. have a function `halts()` into which we pass a program. Function then returns true if halts & false otherwise
  - Only way to know for certain is to run the machine & see what happens. If it halts then you know it halts,, otherwise...?
  - Example of an **undecidable** or **non-computable** problem
- An instance of a class of problems called **decision problems**

# IMPORTANCE OF THE HALTING PROBLEM

- Many computing science (& mathematical) problems are instances of the halting problem in disguise (i.e. they can be reconfigured or *generalised* into a version of the halting problem)
- Halting problem is equivalent to asking:
  - “Does this computer program ever stop?”
  - “Does this computer program have any security vulnerabilities?”
- If had `halts()` then could prove/disprove nearly every open math problem
  - Does an odd perfect number exist?
  - NB. Riemann hypothesis, Goldbach conjecture, Poincare conjecture



# THOUGHT EXPERIMENT

- You have various apps on your mobile device
- Think of each app as a Turing machine
- Sometimes an app crashes your phone because they get caught in a loop and never halt
- Dev team releases an app that checks for this (checker app)
- Checker app takes another app as input, If apps stops then checker app accepts it but If app loops then checker rejects it
- App dev create an app called paradox. It loads the checker app then loads itself into the checker app, e.g. Paradox (Checker ( Paradox)))
- This reverses the output of the checker app. If checker accepts paradox then paradox will loop and crash otherwise it will halt (so the rejection is undeserved),e.g.
  - $\text{Paradox}(\text{Checker}(\text{Paradox})) = \text{Paradox}(\text{Checker}(\text{loop})) = \text{Paradox}(\text{reject}) = \text{Halt}$
  - $\text{Paradox}(\text{Checker}(\text{Paradox})) = \text{Paradox}(\text{Checker}(\text{halt})) = \text{Paradox}(\text{accept}) = \text{Loop}$
- Contradiction

# COMPUTABILITY & COMPUTATION



- Ability to solve a problem in an effective manner
- A problem's computability is closely related to the existence of an algorithm to solve it.
- Have talked about use of Turing machines
- These are powerful computational models but there are less powerful (but still interesting models of computation), e.g. (Non-)Deterministic Finite Automaton, Pushdown Automaton
- Different models can do different tasks, e.g. semantic clarity, easier to implement



# SUMMARY

- Algorithms
- An introduction to complexity (time & space)
- Some practical methods for determining complexity
- A tiny digression into computability





# QUESTIONS ???



IS THIS THE LAST QUESTION?  
(THINK ABOUT IT....)



# WHAT DID WE LEARN?

- *We can now...*
- Inspect code & roughly determine the order of complexity of its computations
- Describe the features & function of the Turing Machine
- Understand some of the limits of computation