Comp 363 - Design and Analysis of Computer Algorithms

Spring Semester 2020 - Week 1

Dr Nick Hayward

Course Details

Lecturer

- Name: Dr Nick Hayward
- Office hours
  - *Tuesday by appointment*
- Faculty Page

Course Schedule

Important dates for this semester

- Project outline and mockup - presentation & demo
  - *Tuesday 11th & Thursday 13th February 2020 @ 10am*
- Spring break
  - ***n.b.*** *no formal class: Tuesday 3rd & Thursday 5th March 2020*
- DEV week: 10th to 19th March 2020
- DEV week - presentation & demo
  - *17th & 19th March 2020 @ 10am*
- Final class: 23rd April 2020
- Final presentation & demo
  - *21st & 23rd April 2020 @ 10am*
- Exam week: 27th April to 2nd May 2020
  - *Final assessment due on 30th April 2020*

Coursework schedule

Presentations, reports &c.

- project outline and mockup
  - *due Tuesday 11th & Thursday 13th February 2020 @ 10am*
- DEV week demo
  - *due Tuesday 17th & Thursday 19th March 2020 @ 10am*
- final team demo
  - *due Tuesday 21st & Thursday 23rd April 2020 @ 10am*
- final team report
  - *due Thursday 30th April 2020*

Initial Course Plan - Part 1

(up to ~ DEV Week)

- intro & review of fundamental concepts
  - *algorithms and data structures*
  - *app development and design patterns*
  - *initial testing of performance*
  - *...*

Initial Course Plan - Part 2

(Up to the end of the semester)

- detailed review of applied usage
  - *algorithms & data structures*
  - *practical use & applications*
  - *app testing and performance*
- integration of algorithms and data structures
  - *problem solving*
  - *app usage*
  - *app context*
  - *...*

Assignments and Coursework

Course will include

- weekly bibliography and reading (where applicable)
- weekly notes, examples, extras...

Coursework will include

- exercises, fun quizzes, and discussions (Total = 40%)
  - *various individual or group exercises and discussions*
- project outline & mockup (Total = 15%)
  - *brief group presentation of initial concept and mockup*
  - *due Tuesday 11th & Thursday 13th February 2020 @ 10am*
- DEV week assessment (Total = 15%)
  - *DEV week: 10th to 19th March 2020*
  - *presentation & demo: Tuesday 17th & Thursday 19th March 2020 @ 10am*
- end of semester final assessment (Total = 30%)
  - *demo due Tuesday 21st & Thursday 23rd April 2020 @ 10am*
  - *final report due Thursday 30th April 2020 @ 10am*

Exercises, fun quizzes, & discussions

Course total = 40%

- exercises
  - *help develop course project*
  - *test course knowledge at each stage*
  - *get feedback on project work*
- discussions
  - *sample problems, articles, applications...*
  - *various contextual concepts and material*
- fun quizzes
  - *various quizzes to reinforce course material*
- extras
  - *code and application reviews*
  - *various other assessments*
  - *peer review of demos*

Development and Project Assessment

Course total = 60% (Parts 1, 2 and 3 combined)

Initial overview

- combination project work
  - *part 1 = project outline & mockup (15%)*
  - *part 2 = DEV Week development & demo (15%)*
  - *part 3 = final demo and report (30%)*
- group project (max. 6 persons per group)
- design and develop an app
  - *purpose, scope &c. is group's choice*
    - NO blogs, to-do lists, note-taking...
    - chosen topic requires approval
    - examples apps include
      - mobile
      - gaming
      - desktop
      - web
      - terminal
  - *must implement algorithms & data structures*

Project outline & mockup assessment

Course total = 15%

- begin outline and design of an application
  - *built from scratch - languages include*
    - JavaScript
    - Python
    - C
    - ...
  - *builds upon examples, technology outlined during first part of semester*
  - *must implement algorithms & data structures*
  - *purpose, scope &c. is group's choice*
  - *NO blogs, to-do lists, note-taking...*
    - chosen topic requires approval
  - *presentation should include mockup designs and concepts*

Project mockup demo

Assessment will include the following:

- brief presentation or demonstration of current project work
  - *~ 5 to 10 minutes per group*
  - *analysis of work conducted so far*
  - *presentation and demonstration*
    - outline current state of app concept and design
    - show prototypes and designs
  - *due Tuesday 11th & Thursday 13th February 2020 @ 10am*

DEV Week Assessment

Course total = 15%

- continue development of application
  - *built from scratch*
  - *continue design and development of initial project outline and design*
  - *working app (as close as possible...)*
  - *NO blogs, to-do lists, note-taking...*
  - *...*
- outline research conducted
- describe data chosen for application
- define algorithms and data structures used in app
  - *why choose these options?*
  - *how have they been used?*
  - *define current performance &c.?*
  - *define testing of implementation & usage*
- show any prototypes, patterns, and designs

DEV Week Demo

DEV week assessment will include the following:

- brief presentation or demonstration of current project work
  - *~ 5 to 10 minutes per group*
  - *analysis of work conducted so far*
    - e.g. during semester & DEV week
  - *presentation and demonstration*
    - outline current state of app
    - explain what works & does not work
    - show implemented designs since project outline & mockup
    - show latest designs and updates
  - *due Tuesday 17th & Thursday 19th March 2020 @ 10am*

Final Assessment

Course total = 30%

- continue to develop your app concept and prototypes
  - *working app*
    - must implement algorithms and data structures
  - *explain design decisions*
    - describe patterns used in design and development of app
    - structures, organisation of code and logic
  - *explain testing and analysis*
  - *show and explain implemented differences from DEV week*
    - where and why did you update the app?
    - perceived benefits of the updates?
  - *how did you respond to peer review?*
  - *...*
- final demo
  - *due Tuesday 21st & Thursday 23rd April 2020 @ 10am*
- final report
  - *due Thursday 30th April 2020*

Goals of the course

A guide to developing applications with algorithms and data structures.

Course will provide

- guide to algorithms and data structures
- guide to developing application structures and patterns from scratch
- integrating algorithms and data structures to solve problems
- best practices and guidelines for development
- fundamentals of application development
    - *practical algorithms and data structures*
- intro to advanced options for app development
- ...

Course Resources - part 1

Website

Course website is available at
https://csteach363.github.io

- timetable
- course overview
- course blog
- weekly assignments & coursework
- bibliography
- links & resources
- notes & material

No Sakai

Course Resources - part 2

GitHub

- course repositories available at https://github.com/csteach363
  - *weekly notes*
  - *examples*
  - *source code (where applicable)*

Trello group

- group for weekly assignments, DEV week posts, &c.
- Trello group - ‘COMP 363 - Spring 2020 @ LUC’
  - *https://trello.com/csteach363*

Slack group

- group for class communication, weekly discussions, questions, &c.
- Slack group - ‘COMP 363 - Spring 2020 @ LUC’
  - *https://csteach363-2020.slack.com*

Group projects

- add project details to course's Trello group, *COMP 363 - Spring 2020 @ LUC*
  - *Week 1 - Project Details*
  - *https://trello.com/b/wRt9MNKN/week-1-project-details*
- create channels on Slack for group communication
  - *please add me to the private channel*
- start working on an idea for your project
- plan weekly development up to and including DEV Week

Intro to Algorithms and Data Structures

- consider their usage in the context of application development
- includes algorithms and data structures
  - *may work together to solve defined problems*
- initially consider an algorithm as a way to solve problems
  - *data structures as a storage option*
- data structure will store the information associated with the problem
  - *work in tandem with the algorithm*
- common use for data structures and algorithms includes data sorting and searching
- basic to many structures
  - *e.g. stacks, queues, priority queues, bags &c.*
- then consider common algorithms for sorting, effective methods for organising data
  - *e.g. quicksort, mergesort, heapsort &c.*
- these algorithms and structures naturally help with search, including classic options
  - *e.g. binary search trees, hash tables &c.*
- may also form part of algorithms for advanced tasks, including
  - *graph traversal and searching*
  - *shortest path algorithms*
  - *minimum spanning trees*
  - *text manipulation and processing*
  - *data compression*
  - *...*

Why algorithms?

- noticeable benefit of algorithms
  - *their scope*
  - *application to many diverse disciplines*
  - *their inherent abstraction*
  - *…*
- broad range of uses, e.g.
  - *internet, science, social networks, video games, music…*
- used in almost every aspect of modern life and culture
- form an invaluable part of scientific research, art, and the humanities

A brief history of algorithms - part 1

- history of algorithms is fascinating to consider
- word itself, *algorithm*, has its roots in the 9th century
  - *with the mathematician Abdullah Muhammad bin Musa al-Khwarizmi*
  - *mathematician, scientist, and astronomer*
- *al-Khwarizmi* is often noted as the father of algebra
  - *the origin of today's word algorithm*
- 12th century Latin translation of a book by *al-Khwarizmi*
  - *provided a translation of his name as Algorithmi*
  - *various alternatives of this story, but the underlying origin is consistent*
- whilst the specific word *algorithm* began with this mathematician and translation
  - *general concept we now associate with an algorithm has ancient roots.*

A brief history of algorithms - part 1

ancient roots

- origin of the use of algorithms may be traced as far back as Babylonian and Egyptian mathematics
- Babylonian and Egyptian mathematics
  - *often considered within the same context of early mathematical usage*
  - *Babylonian system was, in many respects, more advanced*
- e.g. Babylonians were able to work with the following
  - *square and cube roots*
  - *Pythagorean triples - 1200 years before Pythagoras*
  - *knew of the existence of* `pi`
  - *the exponential function, e - possible basic understanding*
  - *solve some quadratics - even polynomials of degree 8*
  - *solve linear equations*
  - *handle measurement of circles*
  - *...*
- their mathematics was not rudimentary and basic
  - *concerned with algebra and not geometry*
  - *an interesting contrast with the later Ancient Greeks*
- Babylonians used a sexagesimal, or `base-60`, number system
  - *inherited from the Sumerians and Akkadians*

A brief history of algorithms - part 1

Babylonian numbers

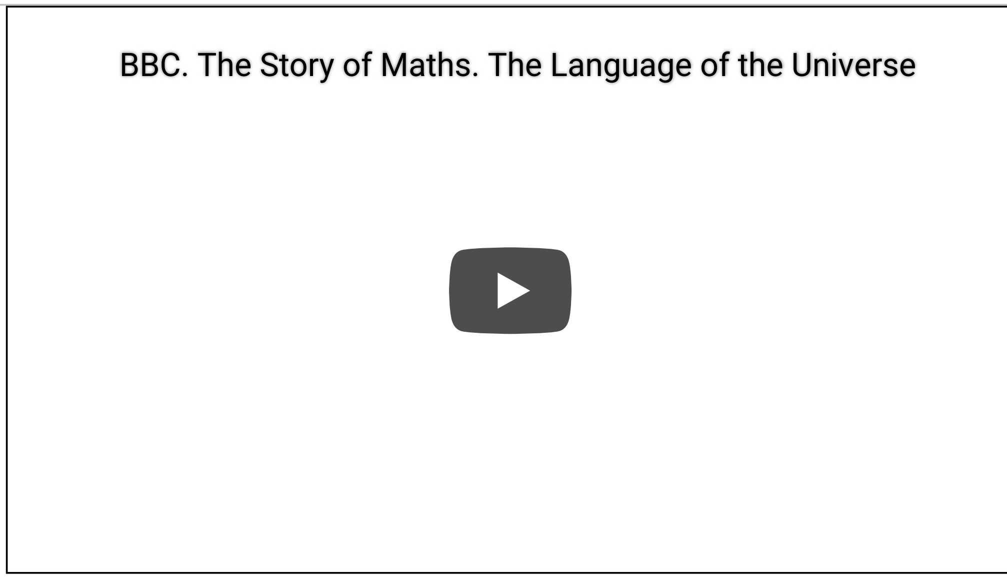
- sexagesimal number system adopted by the Babylonians
  - *used in conjunction with a place value*
  - *used to write numbers larger than 60*
- they had symbols for ‘1 to 59’
  - *then repeated these symbols in additional columns to represent larger numbers*
- simple example is as follows,

column 3	column 2	column 1
2	1	9

- gives us
  - ‘$2(60^2) + 1(60) + 9 = 7269$’
- we may see a basic algorithm at work for their underlying number system

Video - Mathematics

Babylonian numbers



The Story of Maths - Part 1

Source - Story of Maths - YouTube

A consideration of algorithms - part 1

- consider an algorithm as a series of instructions for completing a defined task
- all code that accepts an input, and provides a defined output
    - *may be considered analogous to an algorithm*
- e.g. these patterns may be seen in basic functions
    - *accept a parameter*
    - *commonly return a computed value*
- algorithms come in many different shapes and sizes
- e.g. we commonly use algorithms with
    - *search, graphs, AI and machine learning, gaming, and many more.*
- e.g. for gaming
    - *we might create an algorithm that allows mob objects to track and follow the player using graphs*
    - *might use k-nearest neighbor to define relationships with basic machine learning*
- as we review and develop example algorithms
    - *ommonly perform tests to determine performance, efficiency, speed, and comparative benefits*
    - *such runtime testing is commonly performed using Big-O notation*

A consideration of algorithms - part 2

- we shall cover the key ideas involved in designing algorithms
- how they depend on the design of suitable data structures
- how some structures and algorithms are more efficient than others for the same task
- we'll review a few basic tasks
  - *e.g. storing, sorting, and searching data*
- such tasks underpin much of computer science
  - *equally key to understanding the nature of algorithms*
- we may begin with some key data structures
  - *e.g. arrays, lists, queues, stacks, and trees*
- consider their use in a range of different searching and sorting algorithms
  - *leads to a consideration of efficient storage of data*
  - *e.g. in hash tables*
- also review various graph based representations
  - *covering necessary algorithms for efficient use, navigation, and manipulation*
- we'll investigate computational efficiency of such algorithms
  - *gaining insights on the pros and cons of the various approaches for each task*
- implementing various data structures and algorithms not restricted to particular programming languages
  - *examples will initially be defined in simple pseudocode*
  - *then implemented, where appropriate, in a chosen language*

A consideration of algorithms - part 3

- consider a general search problem, we might initially frame it as
  - *a search problem may be defined as a problem*
  - *requires finding a specific value, a target*
  - *within a space of potential values, a search space*
- we may define a suitable algorithm in the context of target, search space, & search algorithm
- *Target*
  - *piece of data you're searching for...*
  - *target can be either a specific value or a criterion that signifies successful completion of a search*
- *Search space*
  - *set of all possibilities to test for the target*
  - *e.g. search space could be a list of values or all the nodes in a graph*
  - *a single possibility within the search space is called a state*
- *Search algorithm*
  - *set of specific steps or instructions for conducting the search*
- some algorithms will, of course, require additional components, complexities, and considerations
  - *we now have a framing we may use*
  - *e.g. to begin reviewing solutions to the problem*

Algorithms and programs - part 1

> *a finite sequence of instructions, each of which has a clear meaning and can be performed with a finite amount of effort in a finite length of time*

- an algorithm must be precise enough to be understood by us - developers and programmers
- in order to be executed by a computer
  - *generally need a program that is written in a rigorous formal language*
- often a key consideration as we design and test algorithms
- need to define the algorithm abstracted
  - *separate from formalities and depth necessary for a formal implementation in a programming language*
- try to initially reduce the baggage associated with a coded example
- also need to consider relevance of different programming paradigms
  - *e.g. imperative vs declarative*
- Imperative programming
  - *describes computation in terms of instructions that change the program/data state*
  - *common example with JavaScript and direct DOM manipulation*
- Declarative programming
  - *specifies what the program should accomplish without describing how to do it*
  - *e.g. React JS*

Algorithms and programs - part 2

- subtle difference in the examples
  - *imperative commonly defines step by step instructions*
  - *e.g. directly updating an element in the DOM*
  - *declarative with React may define how the element should look, act &c.*
  - *but it doesn't directly update the DOM for the element*
  - *simply defines how it should be rendered &c. for a given state in the app*
- with *declarative*
  - *should not think about how to do achieve a specific result*
  - *instead, consider the result from a given update to state*
- commonly easier to initially understand algorithm design from an *imperative programming* perspective
  - *pseudocode helps us consider this approach without the formal baggage of a given programming language.*
- once a design has been implemented
  - *we may code an example in a chosen programming language*

Algorithms and programs - part 3

code examples

- imperative - plain JavaScript

```
const group = document.getElementById('group');
const btn = document.createElement('button');

btn.className = 'btn red';

btn.onclick = function(event) {
 if (this.classList.contains(‘red’)) {
   this.classList.remove(‘red’);
   this.classList.add(‘blue’);
 } else {
   this.classList.remove(‘blue’);
   this.classList.add(‘red’);
 }
};
container.appendChild(btn);
```

- declarative - React JS

```
class Button extends React.Component{
  this.state = { color: 'red' }
  handleChange = () => {
    const color = this.state.color === 'red' ? 'blue' : 'red';
    this.setState({ color });
  }
  render() {
    return (<div>
      <button
         className=`btn ${this.state.color}`
         onClick={this.handleChange}>
      </button>
    </div>);
  }
}
```

Algorithms and problem solving

- for a *search problem*
  - *some initial, general questions we might consider as we review algorithms to solve a problem*
- e.g.
  - *what is it meant to do?*
  - *does it actually do what it is meant to do?*
  - *how efficient is the algorithm?*
- Or, more formally, we define the following
  - *Specification*
  - *Verification*
  - *Performance analysis*

Algorithms and problem solving

specification

- specification should formalise the essential or pertinent details
  - *i.e. relative to the problem that the algorithm is meant to solve*
- it might be based on a particular representation of the associated data
  - *sometimes it will be presented in a more abstract manner*
- customarily need to define relationship between inputs and outputs of the algorithm
  - *n..b. there is no general requirement that the specification is complete or non-ambiguous*
- for simple problems
  - *often obvious or easy to see that a particular algorithm will always work*
  - *i.e. it will satisfy its specification*

Algorithms and problem solving

verification

- the fact that an algorithm satisfies its specification may not be as obvious
  - *e.g. for more complicated specifications and algorithms*
- need to consider formal verification
  - *to determine whether the algorithm is indeed correct*
- testing on a few particular inputs may be enough to show that the algorithm is incorrect
- as the number of potential inputs, and variety, for most algorithms is infinite
  - *infinite, in theory, and a tad large in practice…*
  - *need to test more than just sample cases to ensure the algorithm satifies the specification*
- need what is commonly known as *correctness proofs*
- we'll briefly discuss *proofs*
  - *and useful relevant ideas such as invariants*
- formal verification techniques are complex
  - *may be considered as an extra topic towards the end of the course*

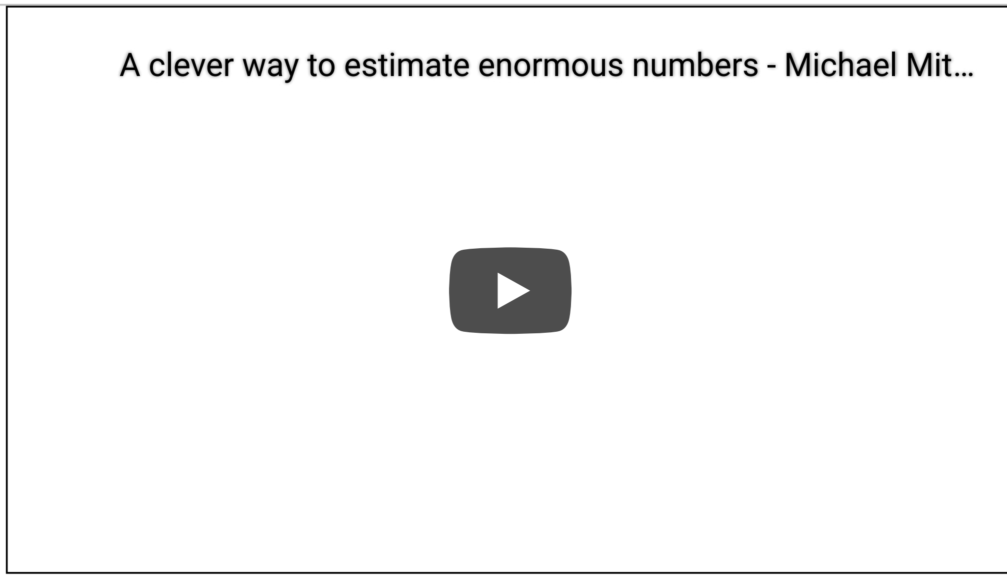
Algorithms and problem solving

performance

- efficiency or *performance* of a given algorithm may relate to the defined *resources* it requires
- e.g. might be relative to how quickly the algorithm runs
  - *or the system resources, such as memory, it requires*
- commonly depends on defined *instance size* of the problem
  - *the chosen representation of data*
  - *the various details of the algorithm itself*
- commonly acted as a useful driving force for development of new data structures and algorithms
- efficiency will be considered in more detail later in the course

Video - Mathematics

fun estimations



A clever way to estimate enormous numbers - Ted-Ed

Source - Ted-Ed - YouTube

Running time for algorithms

- first option for timing algorithms is *simple search*
- in effect
  - *100 items has a potential maximum number of guesses of 100*
- if we increase this number exponentially
  - *potential maximum time will continue to grow at the same rate*
  - *e.g. 4 billion items may take 4 billion guesses to reach the end of the list*
  - *known as linear time*
- if we compare this performance with *binary search*
  - *we quickly see the performance benefits*
- e.g. for a list of 100 items
  - *we require at most 7 guesses*
- larger datasets see a marked improvement in performance
  - *e.g. 4 billion results will now require a maximum of 32 guesses*
- so, we have a comparative result
  - `O(n)` *for linear time*
  - `O (Log n)` *for logarithmic time*

Logarithms

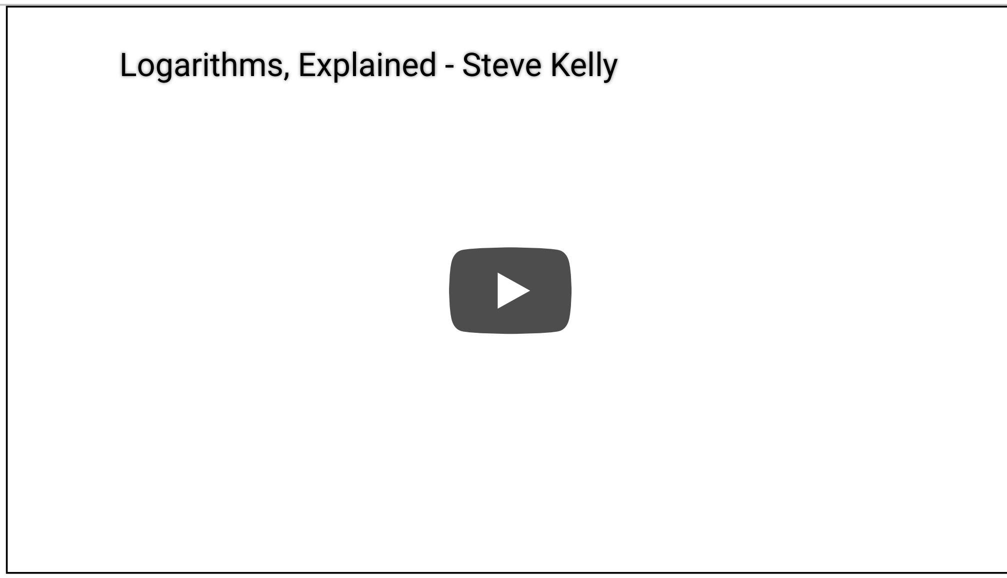
- a brief, but useful segue, on *logarithms*
- commonly consider logs as a flipped implementation of *exponentials*
- e.g.
  - $log_{10}100$
- represents an exponential of 2. or 10 x 10
- in effect,
  - *"how many 10s do we multiply together to get 100?"*
- e.g. we may consider the following examples

exponential	logarithm
$10^2 = 100$	$\log_{10}100 = 2$
$10^3 = 1000$	$\log_{10}1000 = 3$
$2^3 = 8$	$\log_2 8 = 3$
$2^4 = 16$	$\log_2 16 = 4$
$2^5 = 32$	$\log_2 32 = 5$

- running time in Big O notation is commonly referenced as $\log_2$
  - *e.g. log 8 = 3 because 2³ gives us 8.*
- for a list of 1024 elements
  - *test running time as log 1024*
  - *the same as 2¹⁰*
- a search of 1024 elements will require a maximum of 10 queries

Video - Mathematics

Logarithms



Logarithms Explained - Ted-Ed

Source - Logarithms Explained - YouTube

Fun Exercise

example of simple search

- consider examples where *simple search* might be necessary or useful
  - *why?*
  - *where?*
  - *how?*
  - *expected output?*
- then, consider the conditions or information necessary to avoid using simple search…

Approx. 10 minutes and then discuss…

Basic algorithms - binary search

- let's consider an initial example and problem
- Binary search algorithm is a common option
  - *e.g. for finding individual items in a larger dataset*
- we might use this algorithm to find a person in a directory
  - *or, perhaps, find a user in a broader network*
- instead of progressing from A to B to C &c. within a defined directory
  - *we may start in the middle and then divide the data in half*
- division is predicated on an sorted list of data for the binary search algorithm
- as binary search progresses through the dataset
  - *returns index position for a matched result or `null` for no match.*
- helps to eliminate possible results, and continually focus the dataset to find the search criteria

Conceptual example

search for a number

- start with a simple example for guessing a given number from the ordered sequence `1 to 100`
- e.g. pseudocode

```
* first guess is `54`
  * this guess is too low
  * remove all numbers from `1 to 54`
  * number sequence is updated to `55 to 100`
* second guess is `75`
  * this guess is too high
  * remove all numbers from `100 to 75`
  * number sequence is updated to `55 to 74`
* third guess is `65`
  * this guess is too high
  * remove all numbers from `65 to 74`
  * number sequence is updated to `55 to 64`
* fourth guess is `60`
  * this guess is *correct*
```

- by using binary search
  - *may see a stark contrast with the algorithm for simple search*
  - *e.g. compare with linear progression through the numbers until we hit upon the required number or answer*
- e.g. if we consider the above number search
  - *we can easily see how the algorithm optimises performance*
  - *`100 -> 56 -> 20 -> 10 -> 0 - answer found...`*
- binary search has helped us find the correct number in four turns
  - *instead of iterating through each number sequentially*
- a key part of working with binary search is the need to start with an ordered list of data...

Conceptual example

benefits of scale

- a noted benefit of this type of algorithm
  - *the potential to scale for larger datasets*
- as the dataset grows exponentially
  - *the search algorithm is able to keep pace for simple queries*

Working example - binary search

- conceptual design and use of a binary search algorithm
  - *may be implemented in many different programming languages*
- e.g. we might consider the following sample for a Python application

sample - Python binary search

- `binary_search` function
  - *takes a sorted array of items, and a single item*
  - *if item is in the defined array - search function will commonly return its position*
- we may keep a record of where to find a given value

Code example - Python binary search

- start by defining how to track high and low values in a given data set
  - *e.g.*

```
low = 0
high = len(list) -1
```

- as the example searches for a value
  - *keep a record of where to search in the passed array for a given value*
- we may also query the middle of the array
  - *e.g.*

```
mid = (low + high) / 2
guess = list(mid)
```

- then modify these values as we use binary search with the passed dataset
- e.g. if we guess a value for an item
  - *it may be higher, lower, or a known value*
- for a lower value
  - *simply check the current stored value of* `low`
  - *if the guess is too low, update the current low value accordingly*

```
if (guess < item) {
    low = mid + 1
}
```

Big O notation

- Big O is special notation we may use
  - *to test and define the comparative performance of an algorithm*
- e.g. commonly use this notation
  - *to test the performance of a third party algorithm*
- then compare and contrast various algorithms
  - *compare relative to project requirements*

A practical example - part 1

- an example of choosing between simple and binary search
  - *n.b. this may seem like an obvious choice, but there may be contexts where linear time may be acceptable*
- in many examples, we need an algorithm that is both fast and correct
  - *e.g. Landing on Mars…*
- we need to quickly choose an algorithm
  - *usually in 10 seconds or less*
  - *to allow a spaceship to land on Mars*
- for this test
  - *binary search will be quicker for most tests*
  - *simple search is easier to write - may reduce errors due to its inherent simplicity…*
- as we’re performing mission critical tasks, we can’t have any bugs

A practical example - part 2

- begin by running each algorithm 100 times
  - *each task may take 1 millisecond to execute*
- if we run initial tests, we get the following results
  - *simple search = 100 ms (100 x 1ms)*
  - *binary search = 7 ms ($\log_2 100 = 7$)*
- 100 ms vs 7 ms.
- real-world usage difference is minimal
  - *actual program will likely require a billion plus tasks and executions*
- perform a quick initial scaling of timings, e.g.
  - *binary search = ~30 ms ($\log_2 1,000,000,000$)*
- back of the enveleope, panicked calculation...
  - *binary search was initially ~15 times faster, so simple search will scale to* `30 x 15`
- seems reasonable, and is within tolerances for the program

A practical example - part 3

- there's a major issue with this cursory calculation
  - *it's based on an assumption that both search algorithms grow at the same rate*
- run times grow at different rates
  - *thereby impacting performance relative to each dataset*
- if we consider this specific example
  - *Big O notation shows us that binary search is closer to 33 million times faster than simple search*
- so, we *cannot* use simple search for our Mars lander…

Resources

- Babylonian Mathematics
- A clever way to estimate enormous numbers - YouTube
- Declarative programming
- Imperative programming
- Logarithms Explained - YouTube
- React JS
- Story of Maths - YouTube