# 122COM: Profiling and Complexity

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# Overview

1. Profiling
   - Efficiency
   - Optimization
   - Profilers
2. *O*() notation
   - Simple algorithms
   - Good algorithms
   - Bad algorithms
3. Recap

# Efficiency

C

When writing software think about it's efficiency.

- Time.
- Memory.

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- Time.
- Memory.
- Time vs Memory.
  - Can you trade one for the other
  - I.e. data stored in RAM costs memory but saves time.
  - I.e. data stored on hard drive saves memory but costs time.

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- Memory.
- Time vs Memory.
  - Can you trade one for the other
  - I.e. data stored in RAM costs memory but saves time.
  - I.e. data stored on hard drive saves memory but costs time.
- Optimization makes software run faster/leaner/better.

# Optimization

C

*"Premature optimization is the root of all evil"*

–Knuth

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- Test the performance.
  - It may be fine.

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- Write clear, easily understood code. Focus on getting the behaviour right, not on performance.
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- Profile your code to get the baseline performance.
  - So that you know if you are making things better or worse.

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For any large piece of code you should:

- Write clear, easily understood code. Focus on getting the behaviour right, not on performance.
- Test the performance.
  - It may be fine.
- Profile your code to get the baseline performance.
  - So that you know if you are making things better or worse.
- Focus your efforts on the code that is consuming all the time.
  - E.g. small pieces of code that get called multiple times.

# Profiler types

C

Profiling is a method of analysing your code to identify the impact of the different functions/classes/sections etc.

Instrumentation profilers

- Add extra bits of code to track time/memory/function calls.
  - Can be done manually.
  - But automatic is better.
- Accurate.
  - But slows things down.

Statistical profilers

- Regularly checks the software state.
- Accurate-ish.
  - Based on statistical sampling.
  - Doesn't slow things down.

# Example

I

In this example which function takes the most time?

- `fast_math_function()` or `slow_math_function()`?

```
def fast_math_function(a, b):
    time.sleep(0.00001)
    return a + b

def slow_math_function(a, b):
    time.sleep(3)
    return a + b

def main():
    for i in range(int(1.0000)):
        slow_math_function(42, 69)

    for i in range(int(100000)):
        fast_math_function(42,69)

if __name__ == '__main__':
    sys.exit(main())
```

lec_functions.py

# Example

In this example which function takes the most time?

- `fast_math_function()` or `slow_math_function()`?
- Why don't we just profile it and find out?

```
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    return a + b

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if __name__ == '__main__':
    sys.exit(main())
```

lec_functions.py

# Profiler results

I

```
>> python3 -m cProfile lec_functions.py

      200007 function calls in 10.362 seconds

Ordered by: standard name

ncalls tottime percall cumtime percall filename:lineno(function)
     1   0.000   0.000  10.362  10.362 lec_functions.py:1(<module>)
     1   0.137   0.137  10.362  10.362 lec_functions.py:11(main)
100000   0.171   0.000   7.222   0.000 lec_functions.py:3(fast_math_function)
     1   0.000   0.000   3.003   3.003 lec_functions.py:7(slow_math_function)
     1   0.000   0.000  10.362  10.362 {built-in method exec}
     1   0.000   0.000   0.000   0.000 {built-in method exit}
100001  10.054   0.000  10.054   0.000 {built-in method sleep}
     1   0.000   0.000   0.000   0.000 {method 'disable' of '_lsprof.Profiler' obje
```

Things to note:

- Total time - time spent in each function.
- Cumulative time - time spent in each function AND the functions it calls.

# Results visualised

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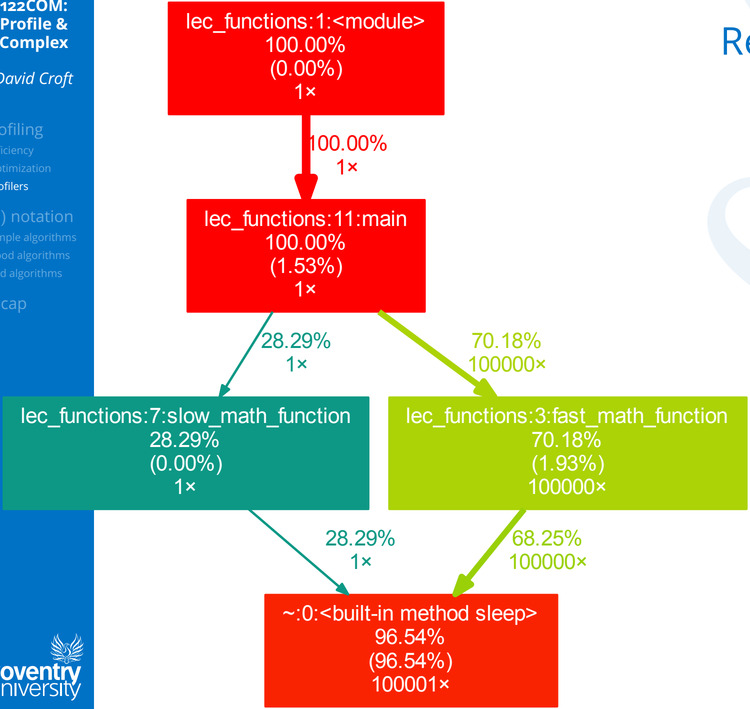



Results passed through Graphviz/gprof2dot.

- A profiling visualisation tool.

# *O*() notation

C

Profiling is very useful in determining the actual performance of your code.

- Unexpected bottlenecks.
- Problems in 3rd party libraries etc.

- Not so good at measuring how code will scale.
  - Change in response to different inputs.
- Algorithmic complexity.
- Certain algorithms are known to be better than other algorithms.

# $O()$ notation

I

Used to describe complexity in terms of time and/or space.

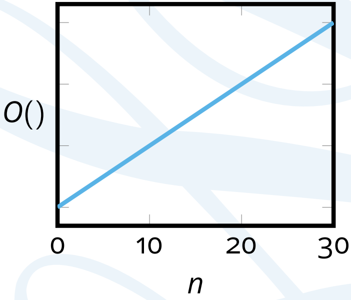
- Commonly encountered examples...
  - $O(1)$, $O(\log n)$, $O(n)$, $O(n \log n)$, $O(n^2)$, $O(2^n)$ and $O(n!)$
- $n$ refers to the size of the problem.
  - E.g. $n$ values to be sorted.
  - E.g. $n$ values to be searched.
- $O()$ notation describes the worst case scenario.
  - Usually, unless otherwise stated.
- $O()$ notation is discussed in detail next year.
  - Main idea is to capture the dominant term: the thing that is most important when the size of the input (n) gets big.

## $O(n)$

C

Linear complexity.

- $n$ is directly proportional to time/space required
  - E.g. $n$ doubles then time/space doubles.
- E.g. linear/sequential search.




```
a = [ 0, 1, 2, 3, 4, 5, 6, 7, 42 ]

for i in a:
  if i == 42:                       (n)
    print('Found it')               (1)
    break                           (1)
```

- So the algorithm takes $n + n + 1 + 1 = 2n + 2$ operations.
  - BUT! We would say it has complexity $O(n)$ as when $n$ gets big the factor or 2 and addition of 2 become irrelevant.

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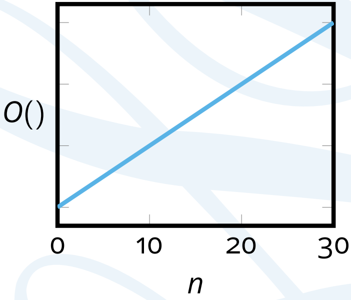


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## $O(1)$

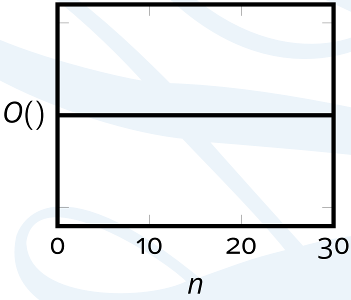
C

Constant complexity.

- $n$ doesn't matter.
- Always takes same time/space.
- E.g. getting first item in an array.

```
a = [ i for i in range(100) ]
b = [ i for i in range(1000000) ]

print(a[0])
print(b[0])
```



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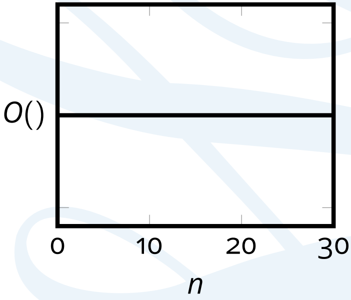

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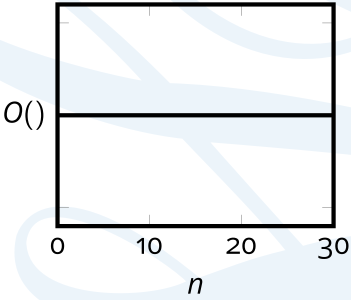

# *O*(1) C

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a = [ i for i in range(100) ]          (n)
b = [ i for i in range(1000000) ]      (m)

print(a[0])                            (1)
print(b[0])                            (1)
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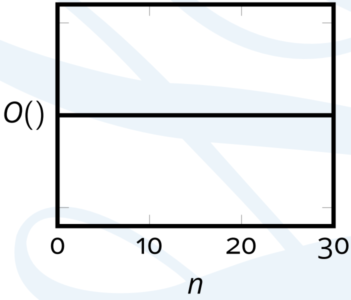


# $O(n^2)$

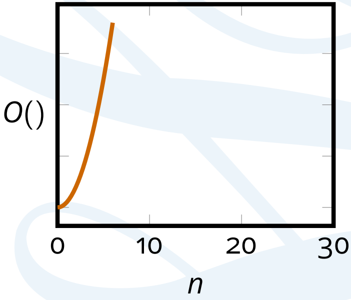
I

Quadratic complexity.

- A lot of simple sorting algorithms are $O(n^2)$.
- Nested `for` loops are common example.
- $O(n^3)$, $O(n^4)$, $O(n^m)$ etc. are all possible.
- Polynomial time.

```python
print('The n times tables')

for i in range(n):
  for j in range(n):
    print(i*j)
```



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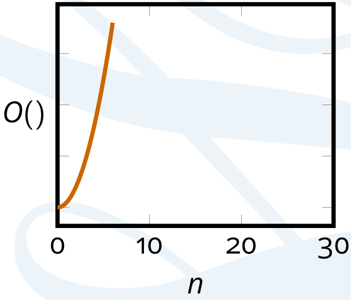

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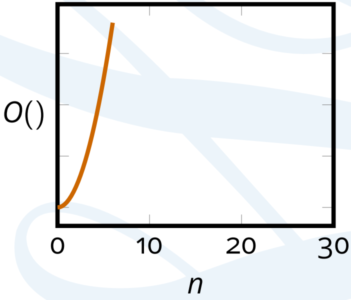

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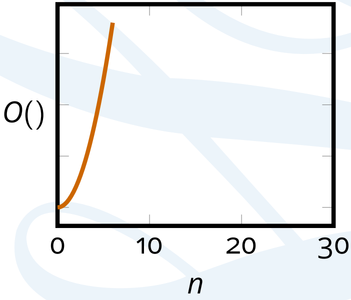

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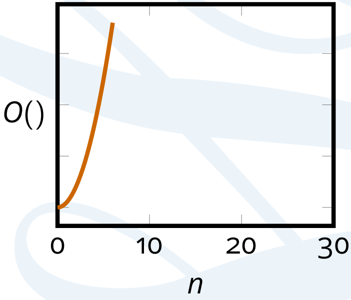
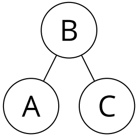


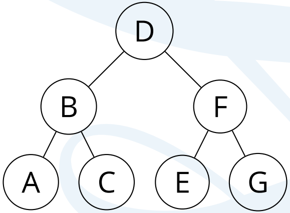
# $O(\log n)$

I

Logarithmic complexity.

- Bit more complicated.
- Binary search.



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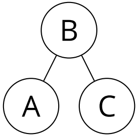
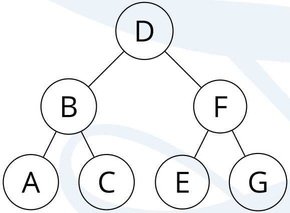



$n = 3$



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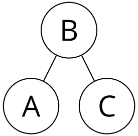
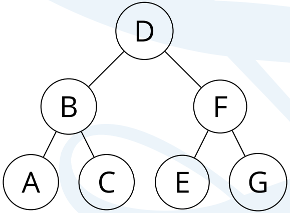



$$n = 3$$
$$O(\log n) = 1.58 \Rightarrow 1$$



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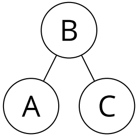


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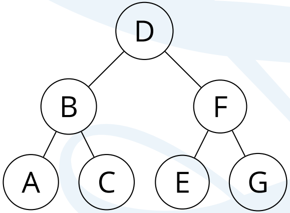


$n = 7$

# $O(\log n)$

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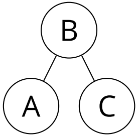


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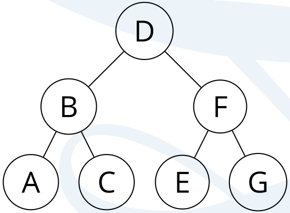


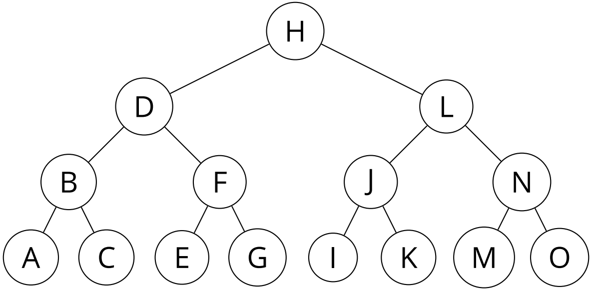

$$n = 7$$
$$O() = 2.81 \Rightarrow 2$$

# $O(\log n)$ cont.

I

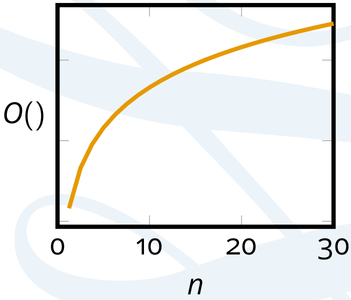
$O(\log n)$ complexity.

- Increases very slowly.
- $\log_2(100)$ is only 6.
- $\log_2(1000000000000)$ (trillion) is only 39.




$n = 15$

$O() = 3.91 \Rightarrow 3$

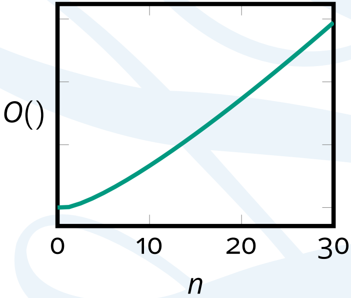


# $O(n \log n)$

A

Loglinear complexity.

- Looks more difficult than it is.
- $O(n \log n)$ means, do $O(\log n)$ $n$ times.
- E.g. binary search for $n$ items.
  - Binary search is $O(\log n)$.
  - Doing $n$ binary searches.
  - So $O(n \log n)$.
- Lots of good sorting algorithms are $O(n \log n)$.

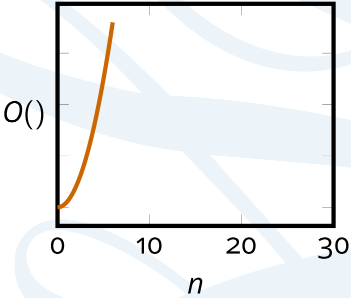


# $O(2^n)$

A

Exponential complexity.

- Very, very bad.
- Each additional value doubles the time/space.
- Doesn't scale.
- $O(3^n)$, $O(4^n)$ etc. are all possible.

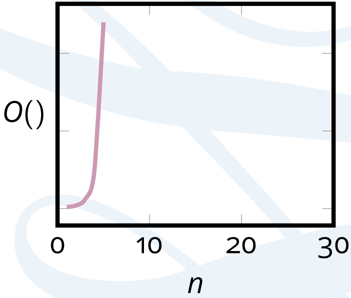


# $O(n!)$

A

Factorial complexity.

- Just awful.
- Every possible combination of $n$ items.
- Brute force travelling salesman is $O(n!)$.
- Totally impractical even for small values of $n$.



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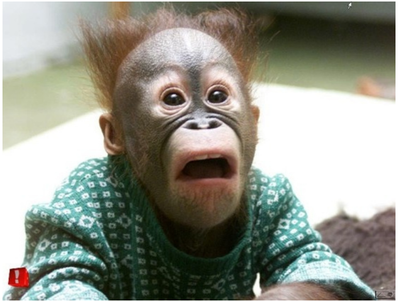
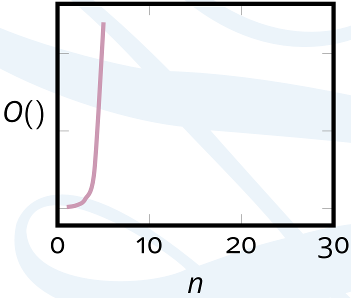




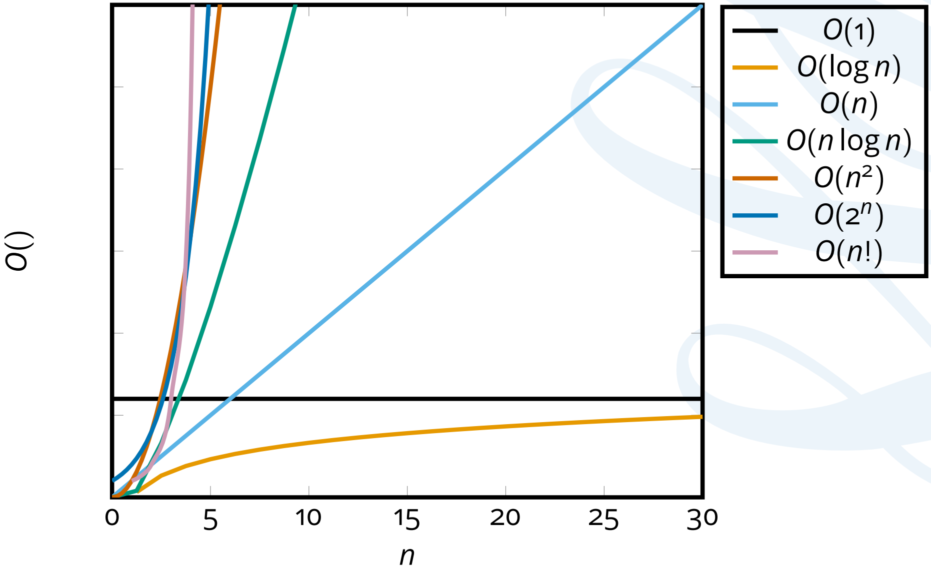
# Scaling

Different $O()$ == wildly different complexity.

| | | $n$ = 2 | 10 | 100 |
|---|---|---|---|---|
| Best | $O(1)$ | 1 | 1 | 1 |
| | $O(\log n)$ | 1 | 3 | 6 |
| $\uparrow$ | $O(n)$ | 2 | 10 | 100 |
| $\downarrow$ | $O(n \log n)$ | 2 | 33 | 664 |
| | $O(n^2)$ | 4 | 100 | 10000 |
| | $O(2^n)$ | 4 | 1024 | $1.27 \cdot 10^{30}$ |
| Worst | $O(n!)$ | 2 | 3628800 | $9.33 \cdot 10^{157}$ |

# Comparison

A



# Complexity vs. Time

I

Complexity isn't the same as efficiency.

- A good $O(n^2)$ implementation can be better than a bad $O(n)$.
  - For a while.
- Eventually, as $n$ increases, $O(n)$ will always outperform $O(n^2)$ etc.

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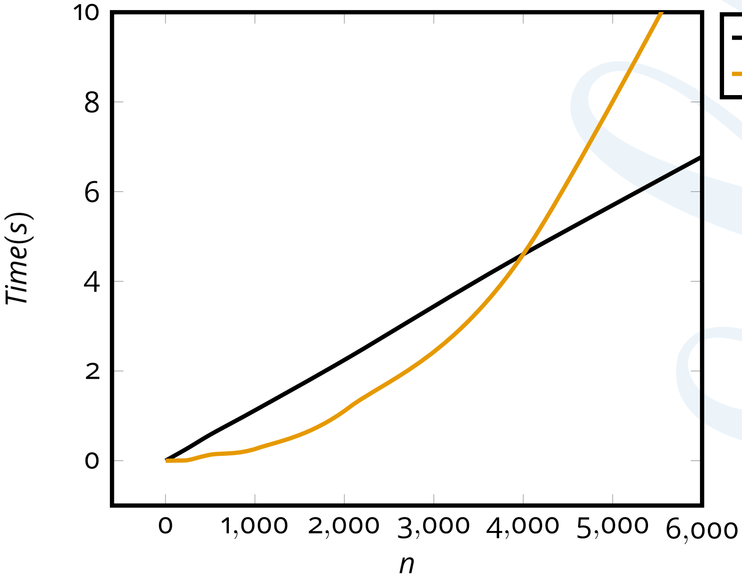
```python
def n_sum(sequence):
    total = 0
    for i in range(len(sequence)):
        total += sequence[i]
        time.sleep(0.001)
    return total
```

lec_fast_slow_functions.py

```python
def n2_sum(sequence):
    total = 0
    for i in range(len(sequence)):
        counter = 0
        while counter < i:
            counter += 1
        total += sequence[counter]

    return total
```

# Time results



# Quiz

# Recap

Profiling help determines the actual performance of your code.

- Statistical profilers.
  - Accurate-ish
- Instrumental profilers.
  - Insert additional instructions.
  - Accurate but slows things down.

$O()$ describes algorithm complexity.

- Time/space.
- How your code should scale.
  - L

ots of real world issues can mess it up.
  - Memory limits etc.
- $O(1) < O(\log n) < O(n) < O(n \log n) < O(n^2) < O(2^n) < O(n!)$
- $\geq O(2^n)$ means exponential.
- $< O(n^2)$ means polynomial.

# The End