

122COM: Profiling and Complexity

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Profiling

Efficiency

Optimization

Profilers

$O()$ notation

Simple algorithms

Good algorithms

Bad algorithms

Recap

1 Profiling

- Efficiency
- Optimization
- Profilers

2 $O()$ notation

- Simple algorithms
- Good algorithms
- Bad algorithms

3 Recap

When writing software think about it's efficiency.

- 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.
- Optimization makes software run faster/leaner/better.

"Premature optimization is the root of all evil"

–Knuth

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.

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.

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?

Example

1

```
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

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

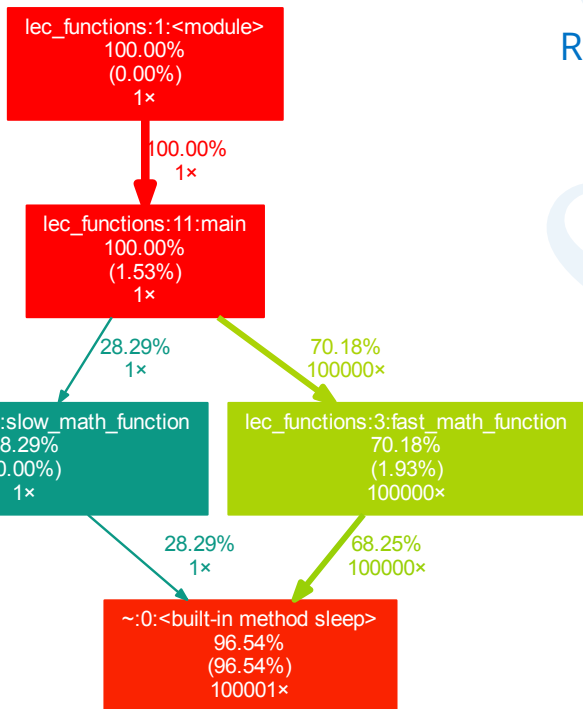
```
200007 function calls in 10.362 seconds
```

```
Ordered by: standard name
```

ncalls	totttime	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' object}

Things to note:

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



Results visualised

C

Results passed through
Graphviz/gprof2dot.

- A profiling visualisation tool.

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.

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

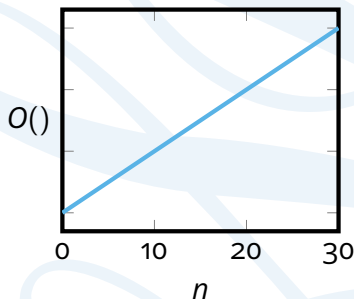
- Commonly encountered examples...
 - $O(1)$, $O(\log n)$, $O(n)$, $O(n \log n)$, $O(n^2)$, $O(2^n)$ and $O(n!)$
- n refers to the size of the problem.
 - E.g. n values to be sorted.
 - E.g. n values to be searched.
- $O()$ notation describes the worst case scenario.
 - Usually, unless otherwise stated.
- $O()$ 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.

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:
        print('Found it')
        break
```

 (n) (n) (1) (1) 

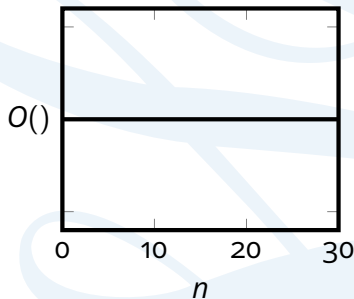
- So the algorithm takes $n + n + 1 + 1 = 2n + 2$ operations.
 - BUT! We would say it has complexity $O(n)$ as when n gets big the factor or 2 and addition of 2 become irrelevant.

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

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

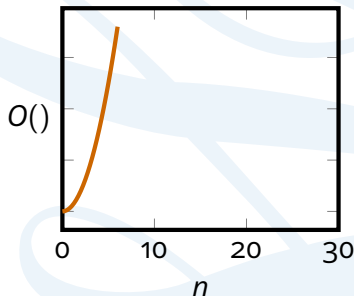


Quadratic complexity.

- 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.

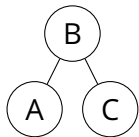
```
print('The n times tables')    (1)

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



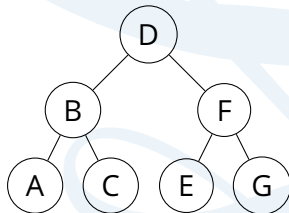
Logarithmic complexity.

- Bit more complicated.
- Binary search.



$$n = 3$$

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

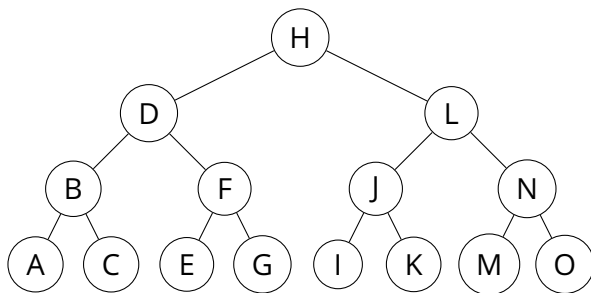


$$n = 7$$

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

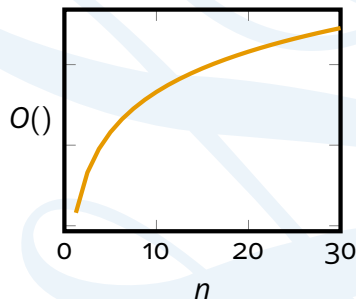
$O(\log n)$ complexity.

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



$$n = 15$$

$$O() = 3.91 \Rightarrow 3$$

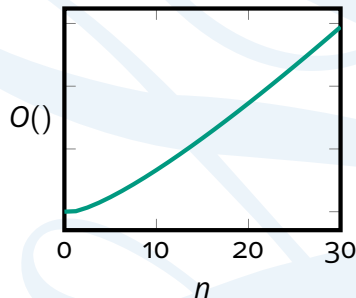


$O(n \log n)$

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 $O(n \log n)$.

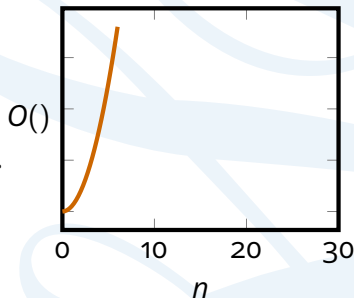


$O(2^n)$

A

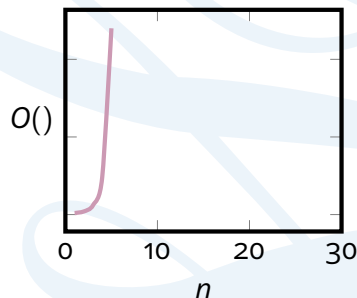
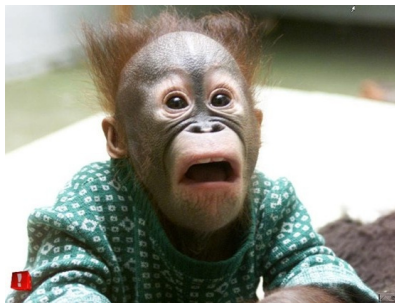
Exponential complexity.

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



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 .





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	$9.33 \cdot 10^{157}$



Complexity vs. Time

1

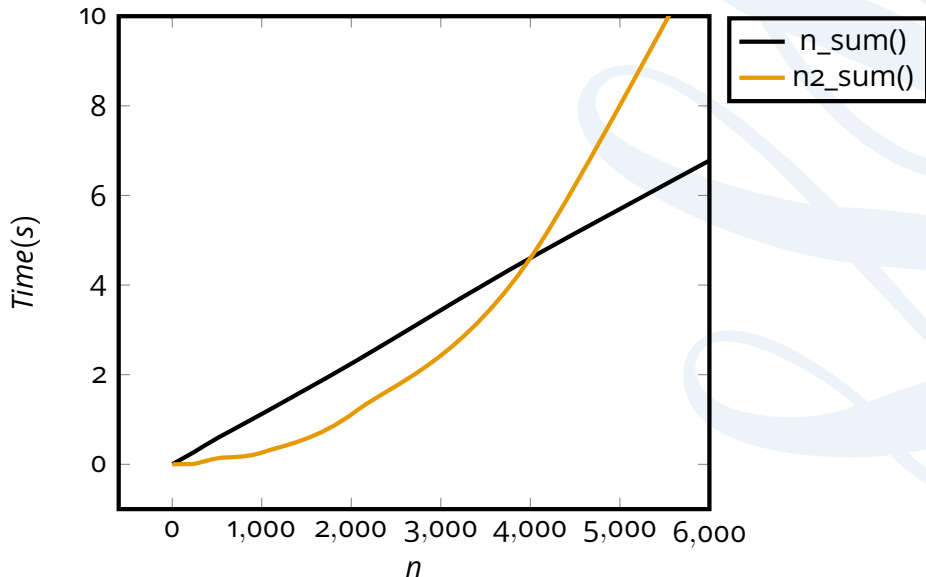
Complexity isn't the same as efficiency.

- 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.

```
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

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



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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.
 - Lots 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.

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The End