

# 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.

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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.

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.

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  - 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.

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()`?

## 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

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

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    for i in range(int(100000)):  
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if __name__ == '__main__':  
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```

lec\_functions.py

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

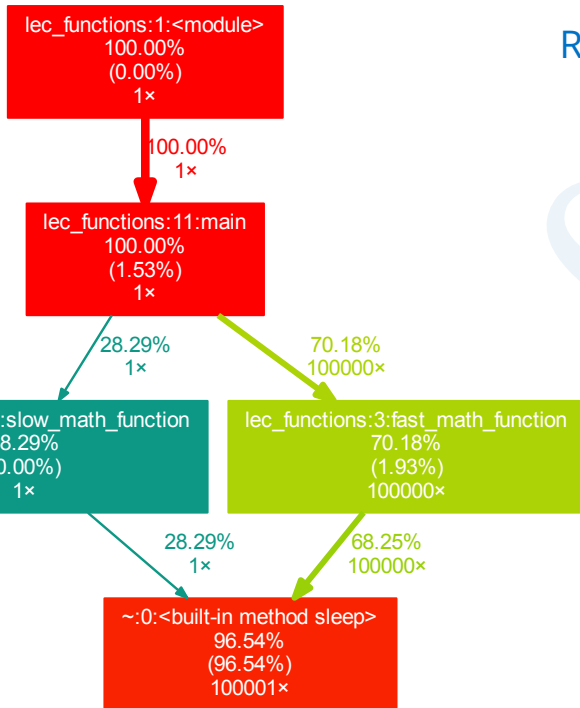
```
200007 function calls in 10.362 seconds
```

```
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 3<sup>rd</sup> 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.

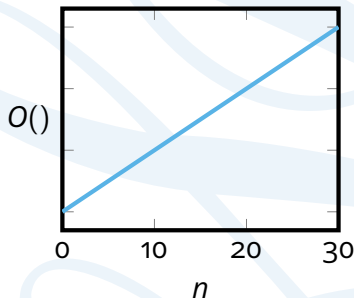
## Linear complexity.

- $n$  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
```

- 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.

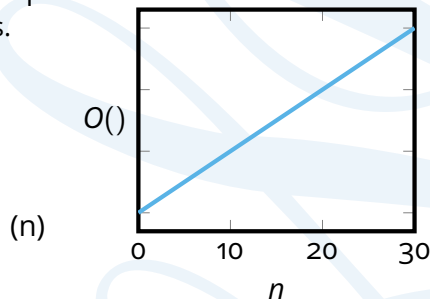


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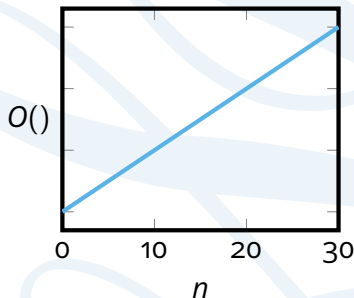
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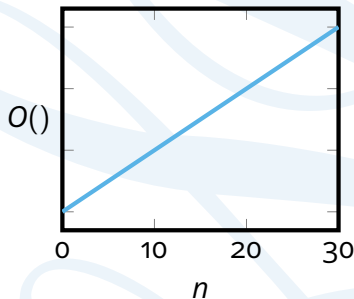
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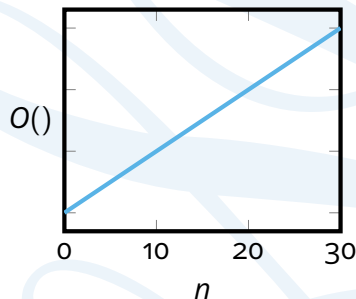
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(1)  
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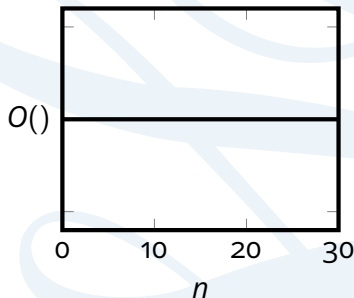
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## Constant complexity.

- $n$  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])
```





$O(1)$ 

C

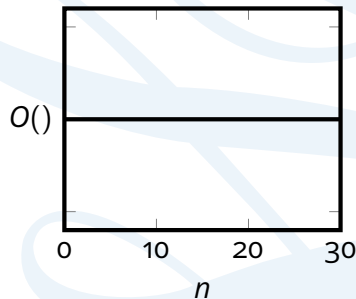
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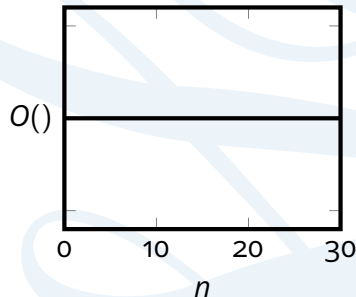
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(1)

```
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(1)

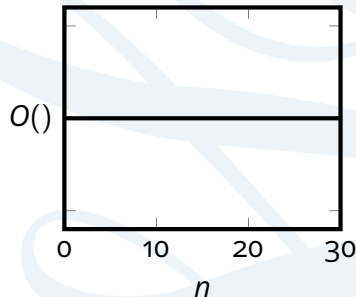


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```
a = [ i for i in range(100) ]      (n)
b = [ i for i in range(1000000) ] (m)

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

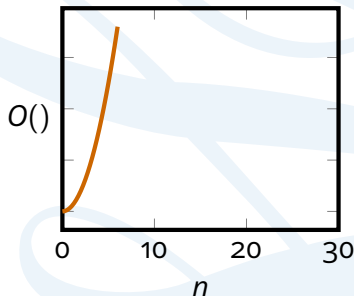


## Quadratic complexity.

- 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')
```

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

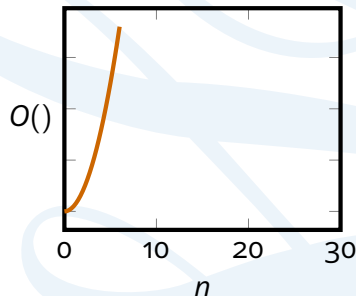


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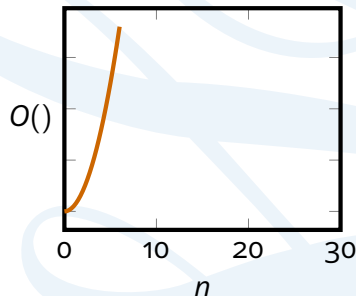


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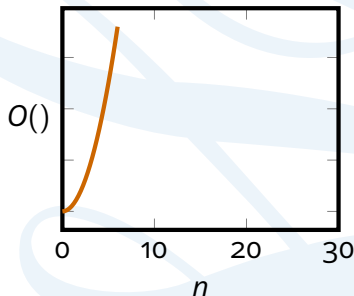


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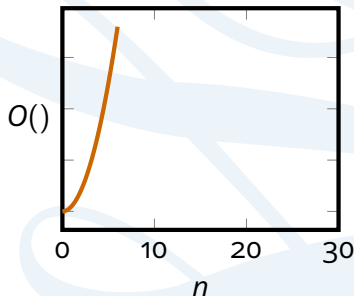


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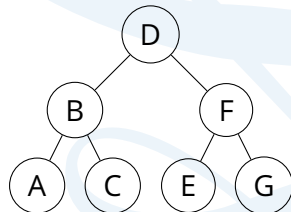
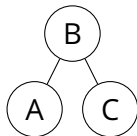
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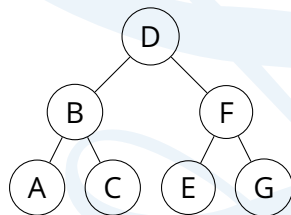
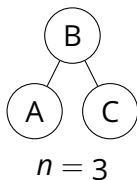
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- Bit more complicated.
- Binary search.



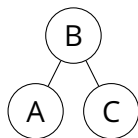
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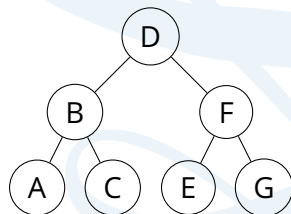
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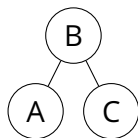
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$$O(\log n) = 1.58 \Rightarrow 1$$



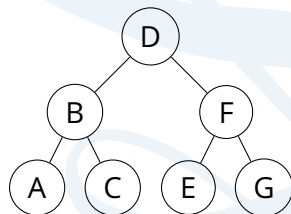
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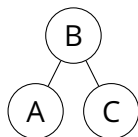
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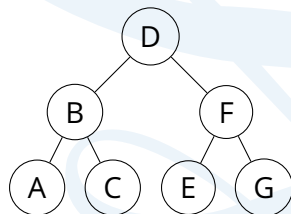
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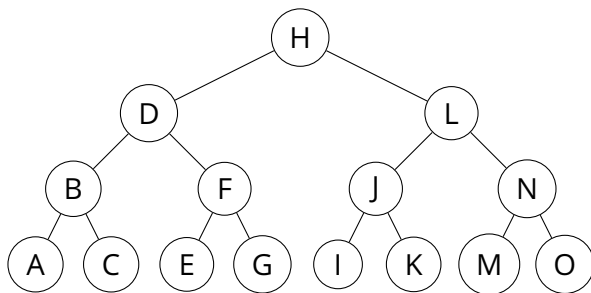
$$O() = 2.81 \Rightarrow 2$$

$O(\log n)$  cont.

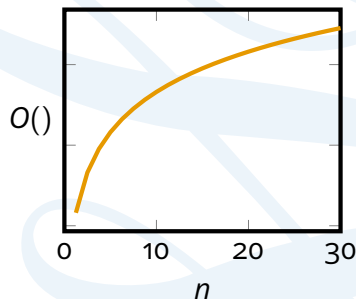
1

 $O(\log n)$  complexity.

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

 $n = 15$ 

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

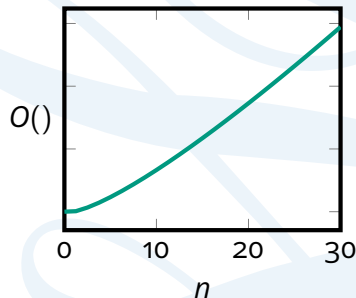


$O(n \log n)$ 

A

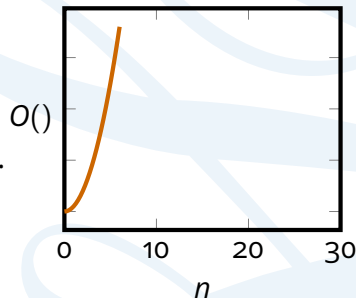
## Loglinear complexity.

- 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  $O(n \log n)$ .



## Exponential complexity.

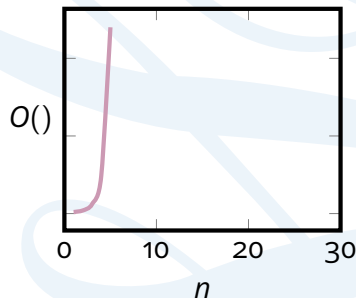
- Very, very bad.
- Each additional value doubles the time/space.
- Doesn't scale.
- $O(3^n)$ ,  $O(4^n)$  etc. are all possible.



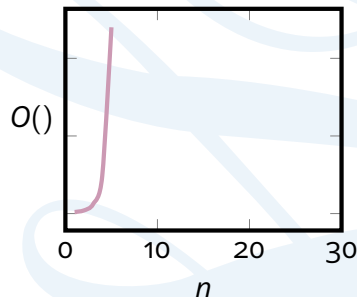
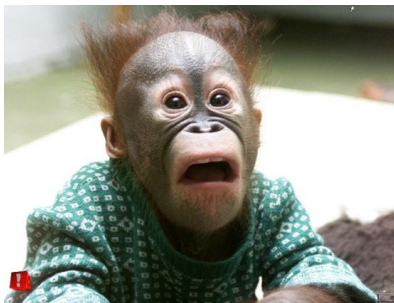


## Factorial complexity.

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



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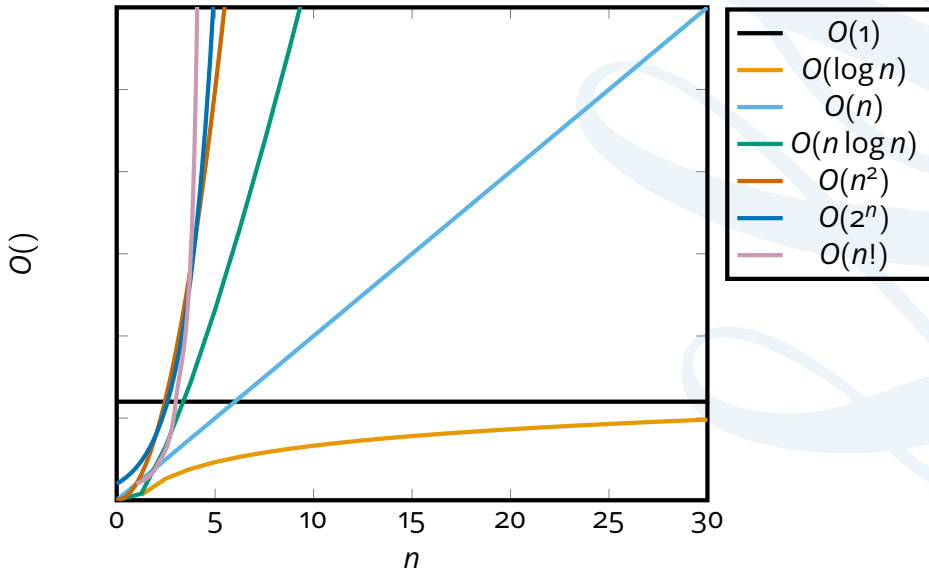


Different  $O()$  == wildly different complexity.

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

## Comparison

A





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.

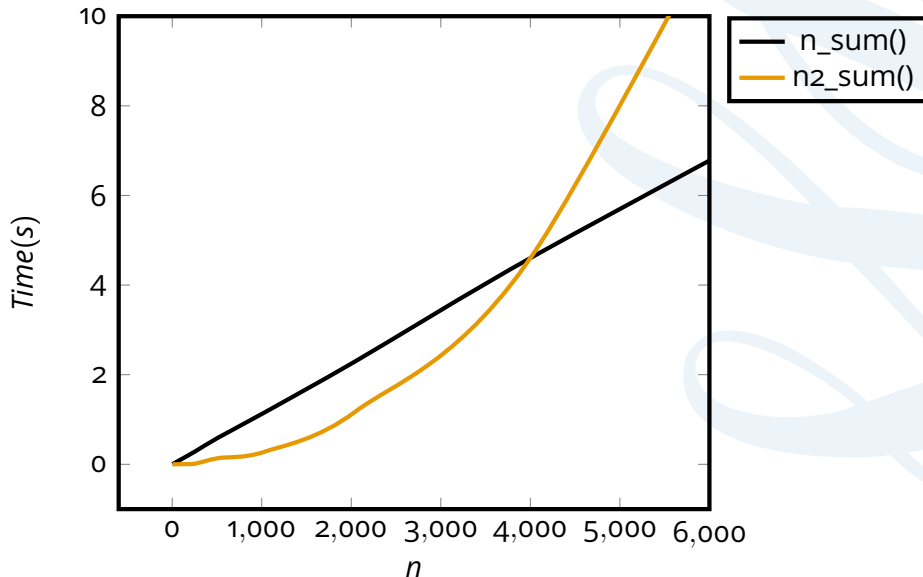
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```
def n_sum(sequence):  
    total = 0  
    for i in range(len(sequence)):  
        total += sequence[i]  
        time.sleep(0.001)  
    return total
```

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
```



Profiling

Efficiency

Optimization

Profilers

$O()$  notation

Simple algorithms

Good algorithms

Bad algorithms

Recap

# 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.

# The End