

Recursive Sorting

CSC148, INTRODUCTION TO COMPUTER SCIENCE

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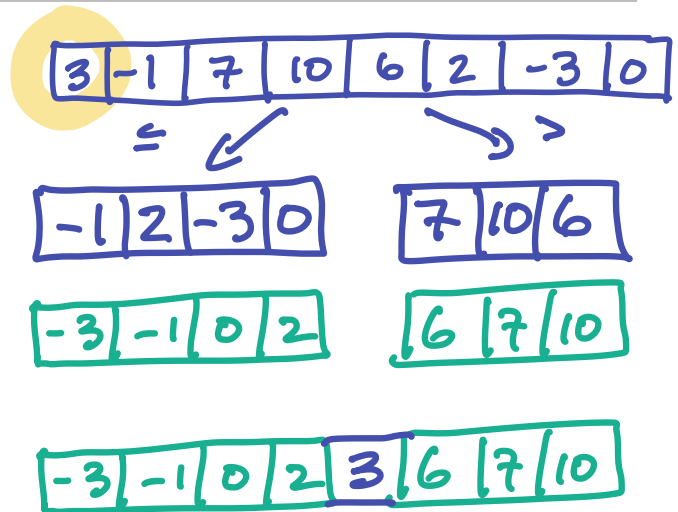
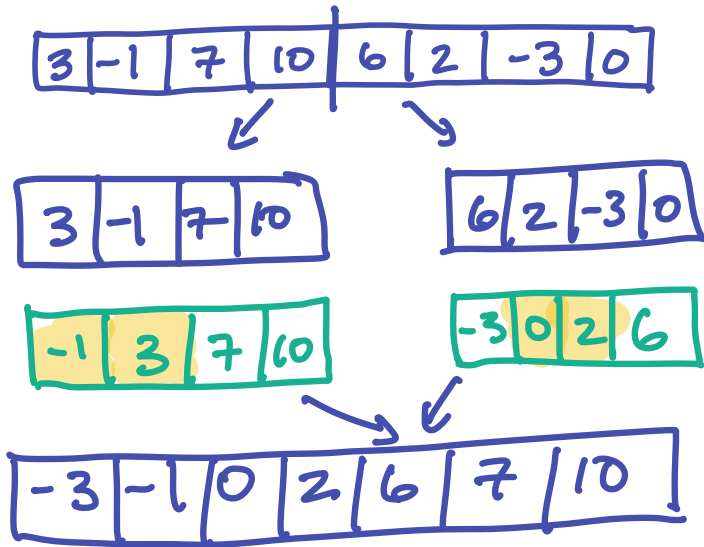
Splitting lists, divide-and-conquer

Mergesort + quicksort both take this strategy:

1. **Divide** the input list into smaller lists.
2. **Recurse** on each smaller list.
3. **Combine** the results of each recursive call.

But how they
divide + re-combine
differs

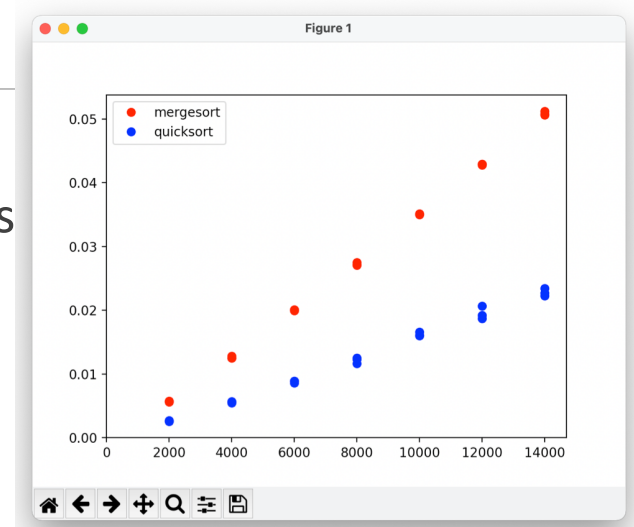
mergesort and quicksort



Running time demo

mergesort, quicksort, and insertion s

*After doing the on-paper analysis,
We ran a demo of these
and generated this
graph :*



Worksheet!

How do we analyse the running time of recursive algorithms in general? (Not just for trees.)

Two key parts:

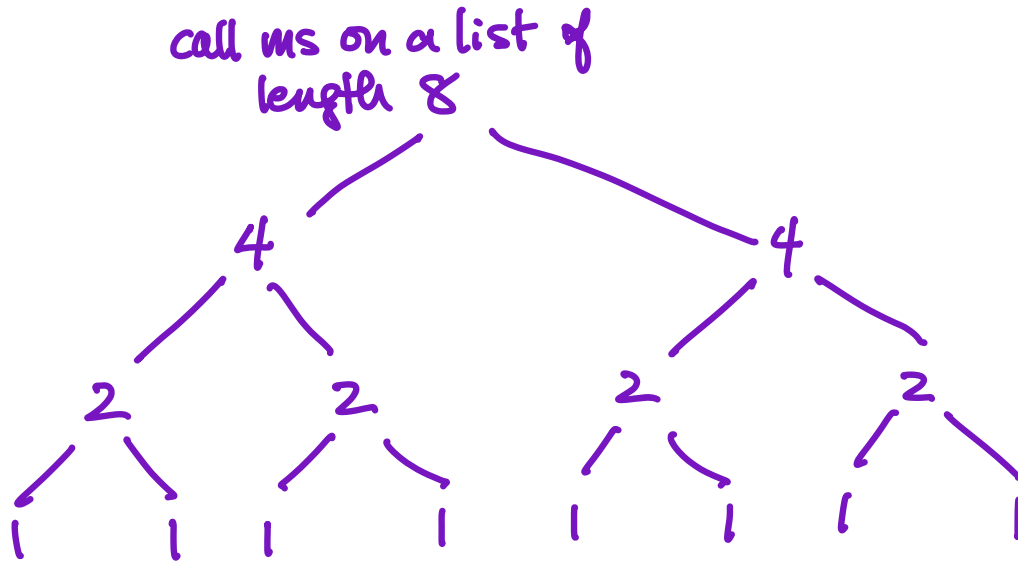
- how long do the *non-recursive parts* take?
- what is the structure of the recursive calls?

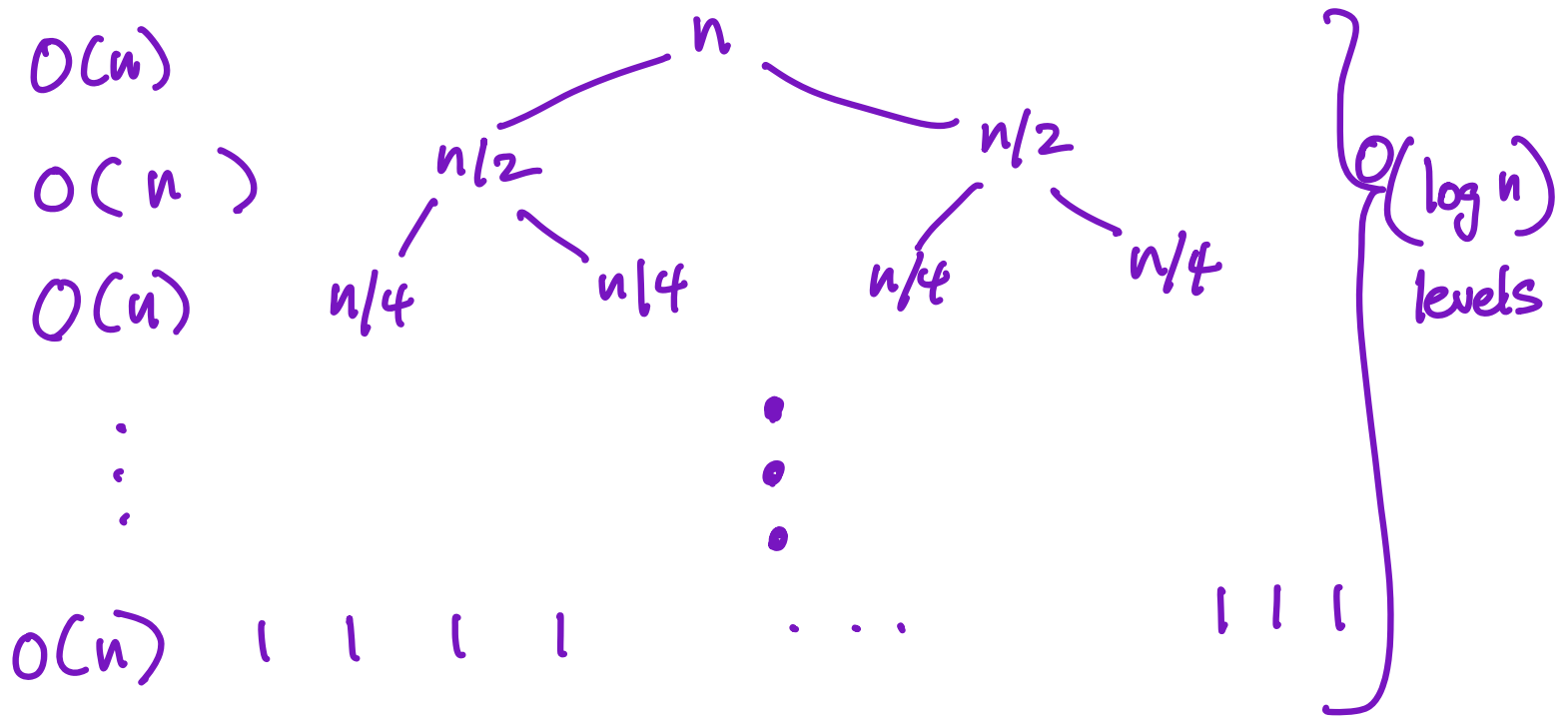
```
def mergesort(lst):  
    if len(lst) < 2:  
        return lst[:]  
    else:  
        mid = len(lst) // 2  
        left = lst[:mid]  
        right = lst[mid:]  
  
        left_sorted = mergesort(left)  
        right_sorted = mergesort(right)  
  
        return _merge(left_sorted, right_sorted)
```

*See worksheet
Q3 + Q5*



Thinking through the recursive calls for mergesort,
with a specific n .





Grand Total : mergesort is $O(n \log n)$

The picture is the same
regardless of list contents

Mergesort doesn't look
at the list to decide
what to do.

It does the same thing
for any list of length n .

∴ $\begin{matrix} \text{worst} & \text{best} \\ \text{case} & = & \text{case} & = & \text{average case for mergesort} \end{matrix}$

See worksheet

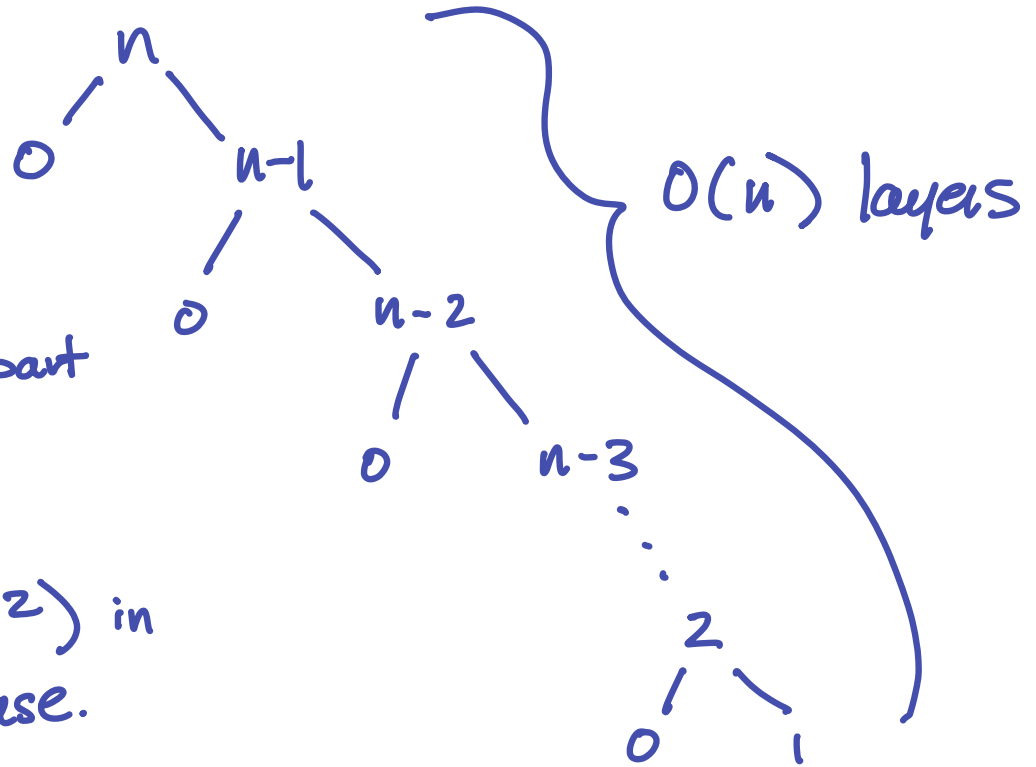
Q1, Q2 + Q6

```
def quicksort(lst):  
    if len(lst) < 2:  
        return lst[:]  
    else:  
        pivot = lst[0]  
  
        smaller, bigger = _partition(lst[1:], pivot)  
  
        smaller_sorted = quicksort(smaller)  
        bigger_sorted = quicksort(bigger)  
  
        return smaller_sorted + [pivot] + bigger_sorted
```

Worst case for Quicksort:

work per layer
for the
non-recursive part
is $O(n)$.

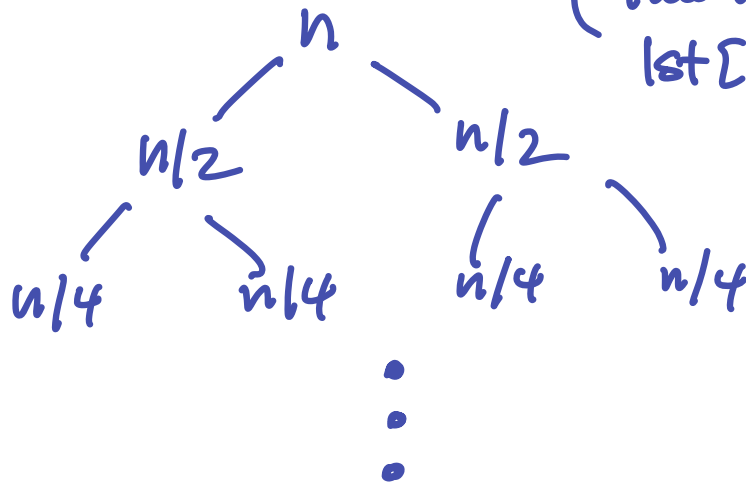
\therefore QS is $O(n^2)$ in
the worst case.



Could it be better? Yes! We could get a complete + balanced tree of calls.

(This happens if, every time, $\text{lst}[0]$, the pivot, is the median.)

Work per level is $O(n)$



Now we have only $O(\log n)$ levels.

1 1 1 1 . . . 1 1 1

\therefore In this case, total work is $O(n \log n)$.



Quicksort: in theory, a mixed bag

If we always choose a pivot that's an *approximate median*, then the two partitions are roughly equal, and the running time is $O(n \log(n))$. *a lot?*
 \equiv mergesort

If we always choose a pivot that's an approximate min/max, then the two partitions are very unequal, and the running time is $O(n^2)$. *worst than mergesort*
rare?

The limitations of Big-Oh

Big-Oh notation is a **simplification** of running time analysis, and allows us to ignore constants when analysing efficiency.

But constants can make a difference, too!

$O(n \log n)$ vs. $O(n \log n)$ vs. $O(n^2)$

???

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On average, QS is $O(n \log n)$

Furthermore, the constants for QS are much smaller than MS.

QS is actually better, on average, than MS.
(See the graph above.)

In-place quicksort

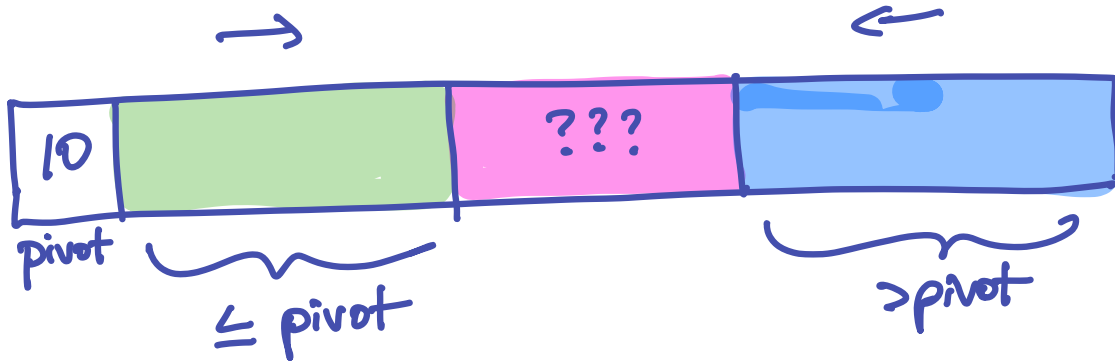
MUTATING THE INPUT LIST IN A SPACE-EFFICIENT WAY.

Example:

<u>10</u>	7	20	30	3	6
10	7	<u>20</u>	30	3	6

10	7	6	30	3	20
10	7	6	<u>30</u>	3	20
10	7	6	3	30	20
10	7	6	3	30	20

The key helper: in-place partition



```
def quicksort(lst):  
    if len(lst) < 2:  
        return lst[:]  
    else:  
        pivot = lst[0]  
  
        smaller, bigger = _partition(lst[1:], pivot)  
  
        smaller_sorted = quicksort(smaller)  
        bigger_sorted = quicksort(bigger)  
  
        return smaller_sorted + [pivot] + bigger_sorted
```

Simulating slicing with indexes

We often want to operate on just part of a list:

- `f(lst[start:end])`

Rather than create a new list object, we pass in the indexes:

- `f(lst, start, end)`

Simulating slicing with indexes

`_in_place_partition(lst) →`
`_in_place_partition(lst, start, end)`

`quicksort(lst) →`
`_in_place_quicksort(lst, start, end)`

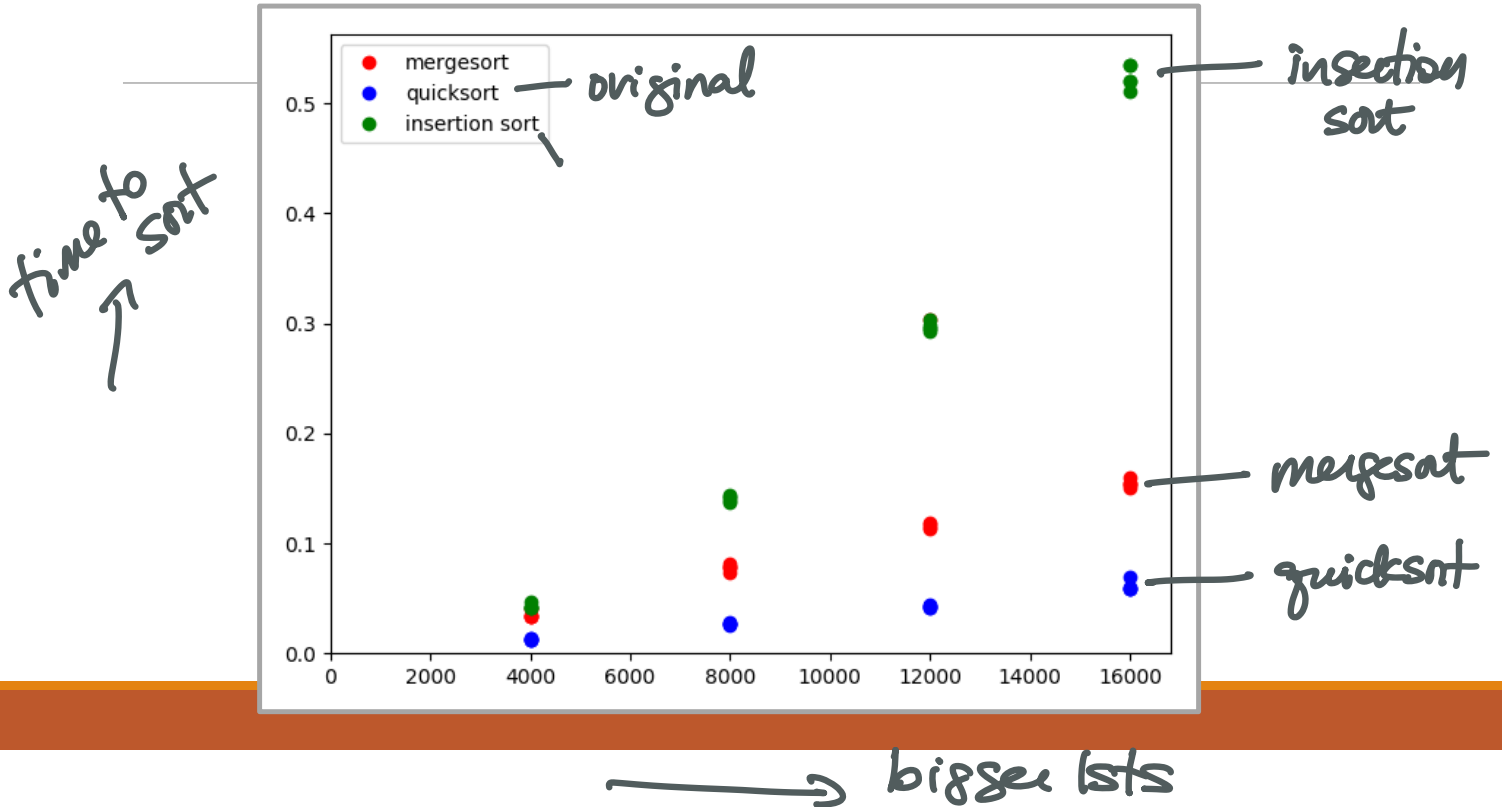
Lessons in efficiency

A CASE STUDY IN COMPARING SORTING ALGORITHMS



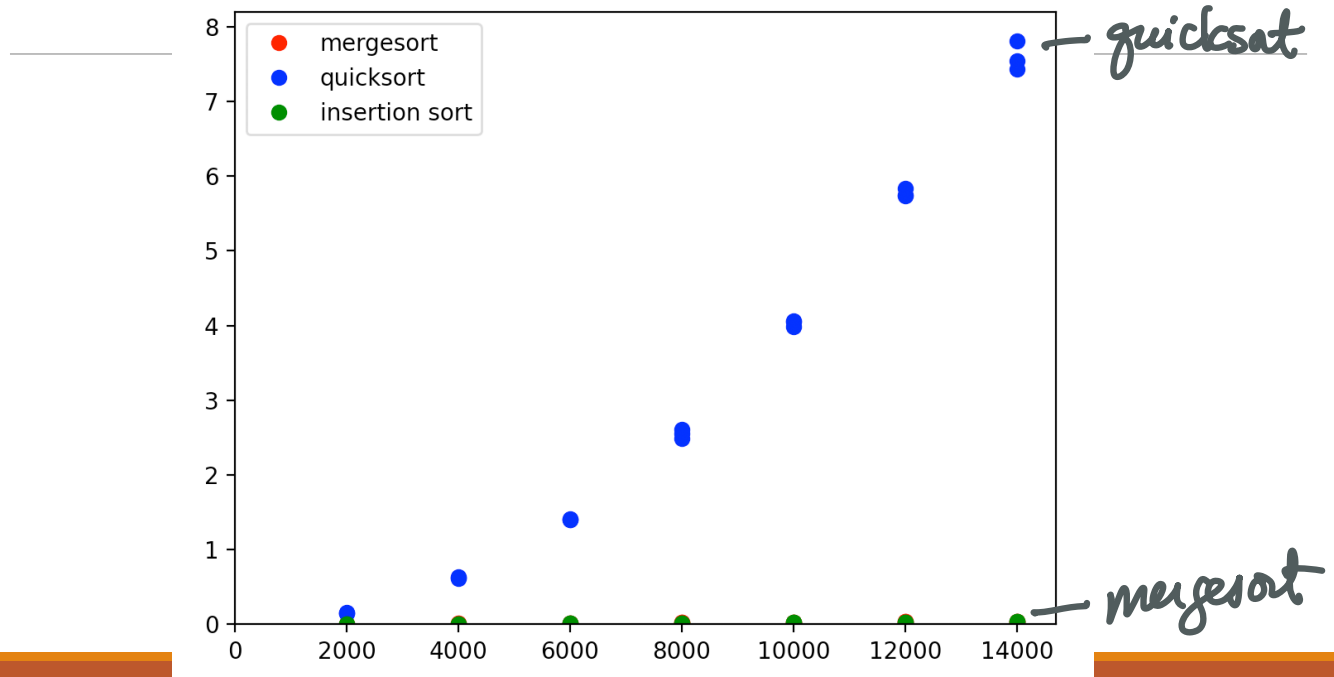
Shuffled input

1. Big-Oh describes behaviour as input size grows

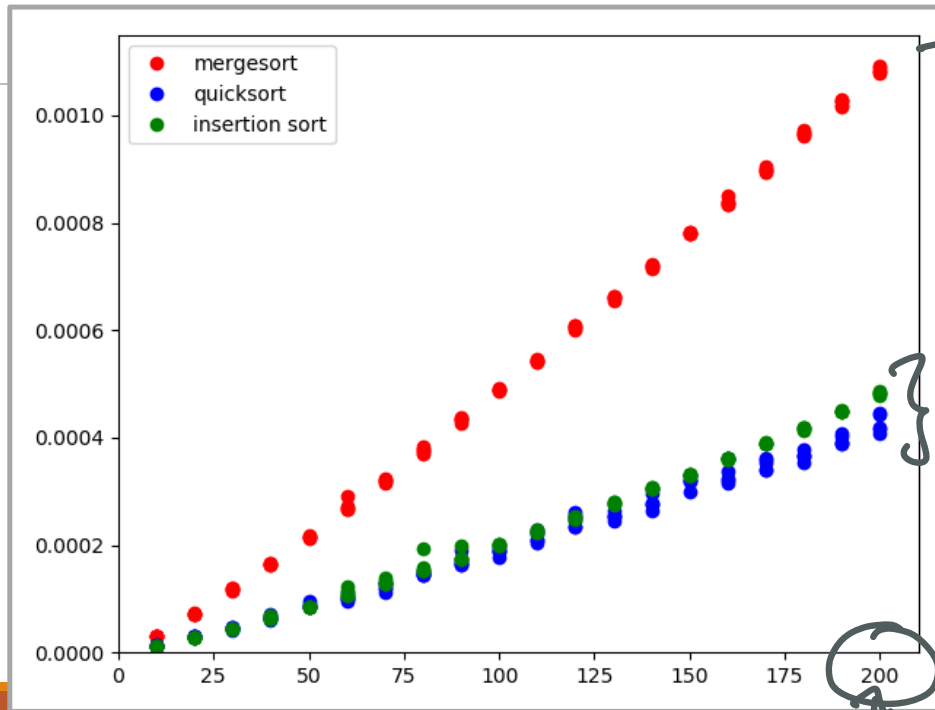


Sorted Input

2. An algorithm can be “good on average” and “bad in the worst case”

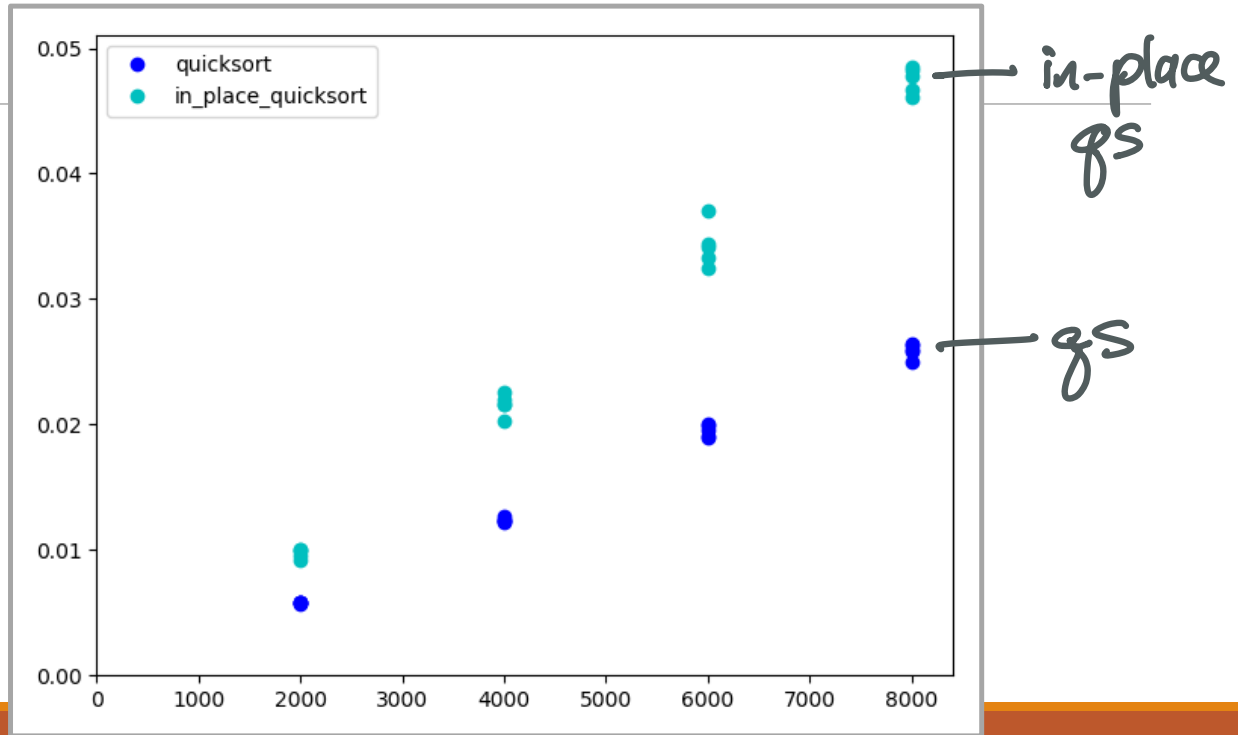


3. Big-Oh is *not* good at predicting behaviour on small inputs.

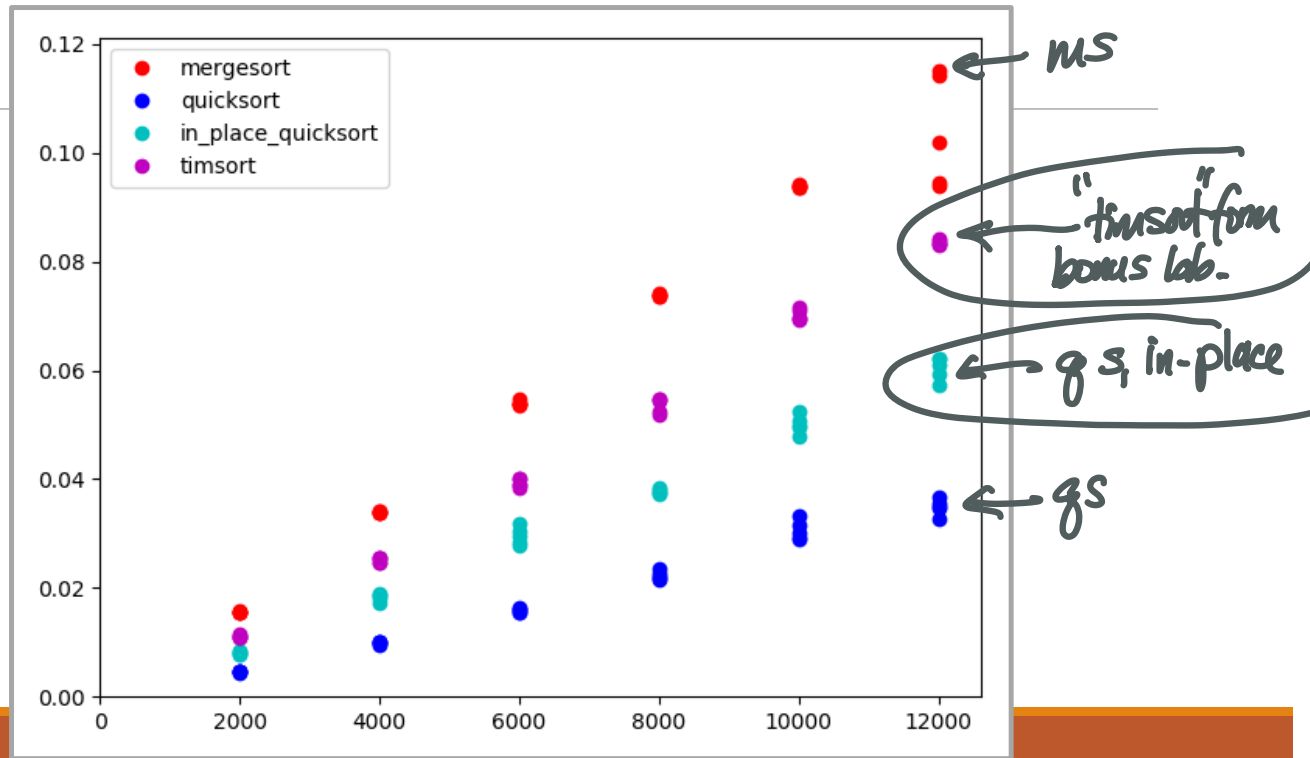


How did we do - with all that effort
to work in place ?

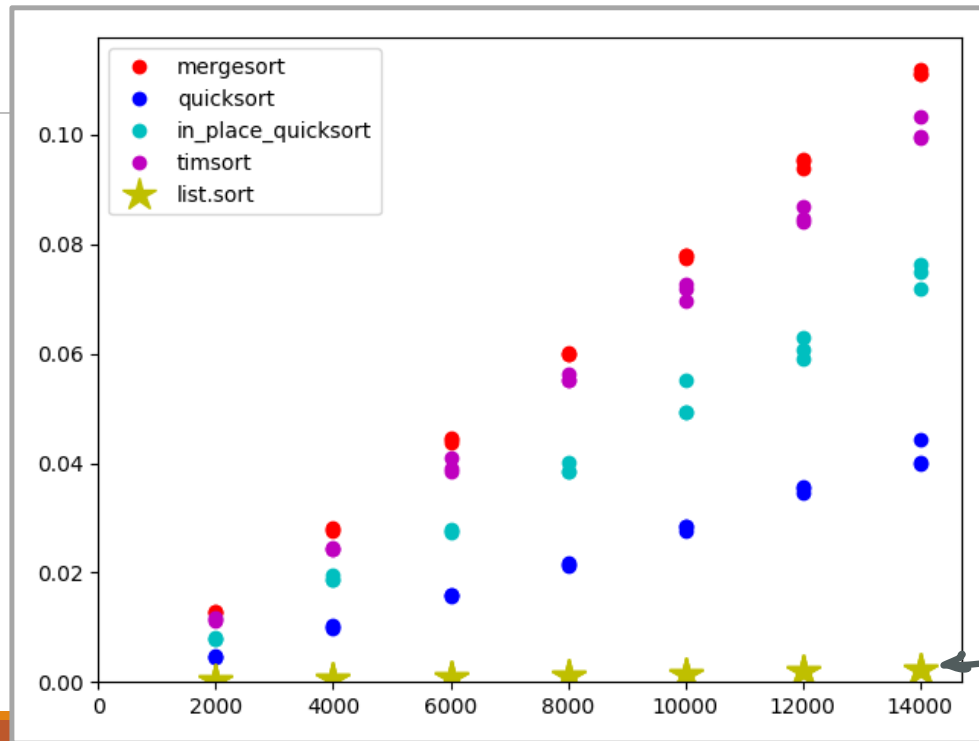
4. Saving space doesn't always mean saving time!



5. Hard work doesn't always mean saving time, either!



6. But sometimes hard work pays off.*



list.sort!