COMS10017 - (Object-Oriented Programming and) Algorithms

Dr Christian Konrad

```
Require: array A of length n

if n \le 1 then

return A

else

i \leftarrow Partition(A)

QUICKSORT(A[0, i - 1])

QUICKSORT(A[i + 1, n - 1])
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Algorithm QUICKSORT

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Partition A around a Pivot:

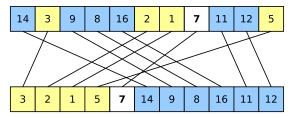
14	3	9	8	16	2	1	7	11	12	5	
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|--|

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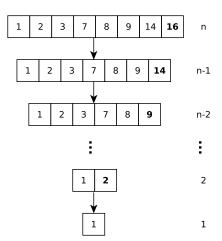
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$$n_1 = \lfloor \frac{n-1}{2} \rfloor$$
, $n_2 = \lceil \frac{n-1}{2} \rceil$

Partition:

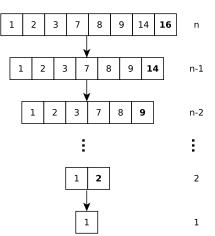
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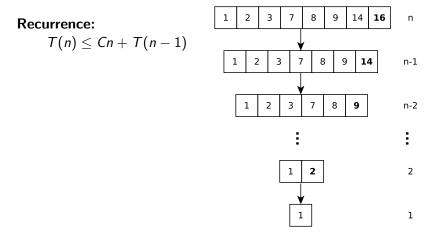


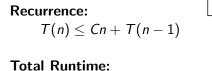
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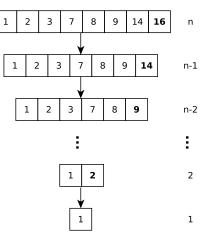
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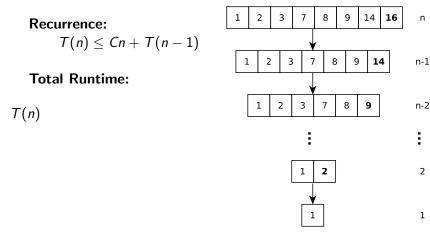
Recurrence:



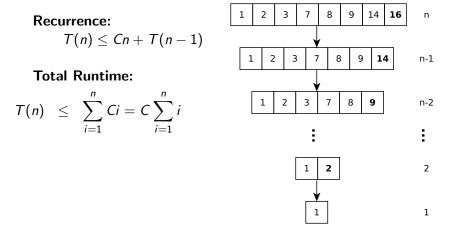






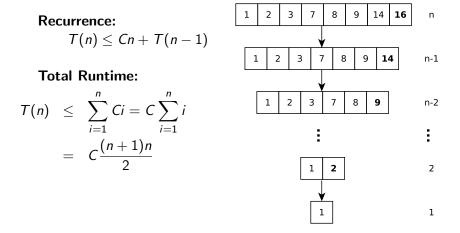


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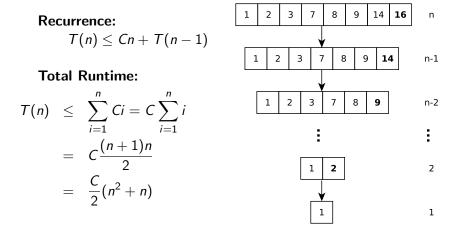


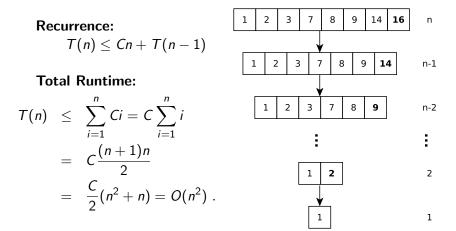
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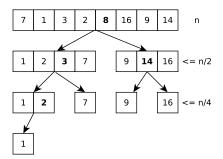


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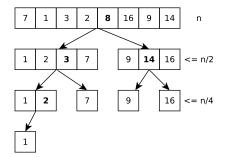




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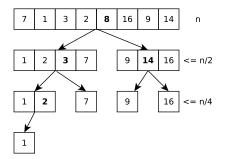


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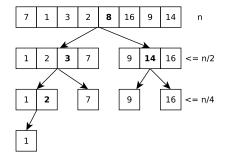
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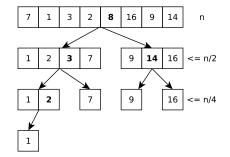


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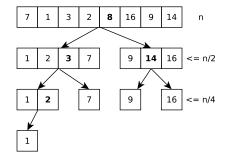
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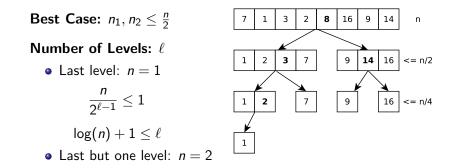
$$\frac{n}{2^{\ell-1}} \le 1$$

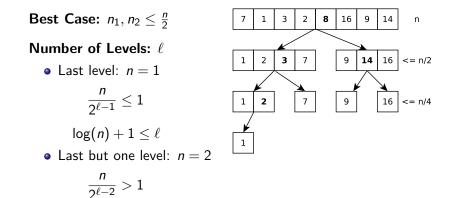


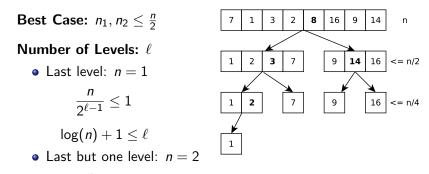
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$$\frac{n}{2^{\ell-1}} \le 1$$
$$\log(n) + 1 \le \ell$$

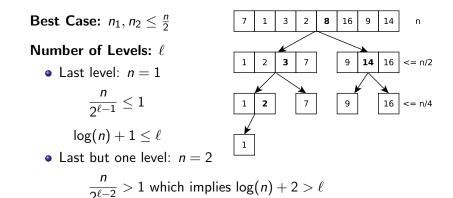




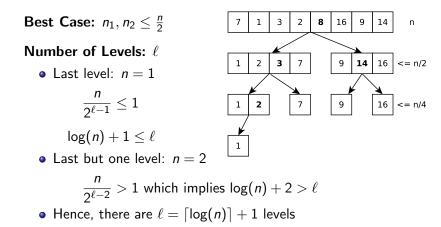




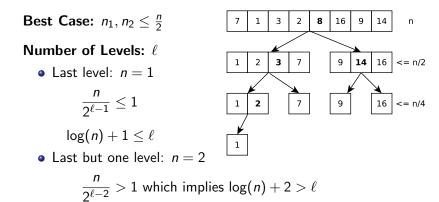
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 which implies $\log(n) + 2 > \ell$



• Hence, there are $\ell = \lceil \log(n) \rceil + 1$ levels



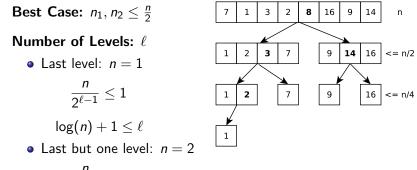
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• Observe: Total runtime of Partition() in a level: O(n)



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- Observe: Total runtime of Partition() in a level: O(n)
- Total runtime: $\ell \cdot O(n) = O(n \log n)$.

• It is crucial that subproblems are roughly balanced

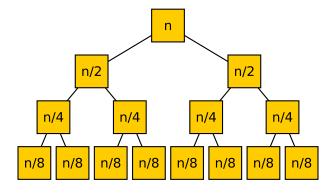
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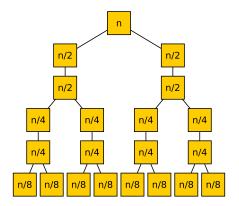
Good versus Bad Splits: Intuition and Rough Analysis



. . .

Only good splits: Recursion tree depth $\lceil \log n \rceil + 1$

Good versus Bad Splits: Intuition and Rough Analysis



Good & bad splits alternate: Recursion tree depth $2 \cdot (\lceil \log n \rceil + 1)$

Selecting good Pivots

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Idea that works in Practice: Select Pivot at random! (Implementation: exchange A[n-1] with a uniform random element A[i])

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If we select the pivot randomly, how likely is it to have a bad split?

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Random Pivot Selection: QUICKSORT runs in expected time $O(n \log n)$ if the pivot is chosen uniformly at random