CS11313 - Spring 2022 Design & Analysis of Algorithms

Selection

Ibrahim Albluwi

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Answer 4. Construct a heap and run *m* iterations of Heapsort. Take the last *m* elements in the array. Running time: $\Theta(n)$ for heap construction + $O(m \log n)$ for the *m* iterations = $O(n + m \log n)$

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- Repeated selection leads to sorting.
- If the array is sorted, selection is easy!

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Candidate Solutions.

- Perform *k* iterations of selection sort. $\leftarrow \Theta(kn)$
- Insert the elements into a binary heap data structure. $\leftarrow O(n \log n)$
- Sort and then get the element at index k. $\leftarrow O(n \log n)$ if heapsort is used.
- Heapify and then remove *k* elements from the heap. $\leftarrow O(n + k \log n)$.

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Can we do better?

Is selection as hard as sorting? (requires ~ $n \log n$ compares in the worst case if $k = \frac{n}{2}$)




























SELECT(a[], first, last, k)

SHUFFLE(a, first, last)
QUICK-SELECT(a, first, last, k)

to guard against the worst case (or pick pivot randomly)

assuming *k* is a valid index

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```
if (first >= last):
    return a[k]
```

```
p = PARTITION(a, first, last)
```

```
if p == k:
```

```
if k > p:
```

```
return QUICK-SELECT(a, p+1, last, k)
else:
```

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return QUICK-SELECT(a, first, p-1, k)
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Best Case.

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 $n + (n - 1) + (n - 2) + \dots + 1 = \Theta(n^2)$

Example 1. k = n - 1



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probabilistically almost-
impossible if the array is
shuffled!

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Expected Case. $\Theta(n)$

Intuition. Partitioning always gets rid of around half of the remaining elements.

$$T(n) = T(\frac{n}{2}) + \sim n$$

time to select from an array of size *n*

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$$T(n) = T(\frac{n}{2}) + \sim n \quad \qquad \text{time to partition an} \\ array of size n \\ \text{time to select from} \\ f = 1$$

an array of size n

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$$n$$
time to partition
the whole array

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$$n + \frac{n}{2}$$
time to partition
half the array

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$$T(n) = T(\frac{n}{2}) + \sim n$$

$$n + \frac{n}{2} + \frac{n}{4}$$
time to partition

a quarter of the array

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Remember!

$$\sum_{i=0}^{\log_2 n} 2^i = 2^{\log_2 n + 1} - 1 = 2n - 1$$

$$1 + 2 + 4 + 8 + \dots + n$$

= 2⁰ + 2¹ + 2² + 2³ + \dots + 2^{log_2n}

$$n + \frac{n}{2} + \frac{n}{4} + \dots + 4 + 2 + 1$$

$$n \times (1 + \frac{1}{2} + \frac{1}{4} + \dots + \frac{1}{n})$$

n -1 internal nodes in a complete tree of height log₂ *n*





 ≤ 2

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Analysis Notes

Remember: Code that follows the pattern below has a running time of $\Theta(n \log n)$



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Can we do better?

Theoretically. Selection can be done in linear time in the worst case using the Median of Medians algorithm. (Blum, Floyd, Pratt, Rivest, and Tarjan 1973).

Practically. Quickselect is faster in practice.


Introselect

From Wikipedia, the free encyclopedia

In computer science, **introselect** (short for "introspective selection") is a selection algorithm that is a hybrid of quickselect and median of medians which has fast average performance and optimal worst-case performance. Introselect is related to the introsort sorting algorithm: these are analogous refinements of the basic quickselect and quicksort algorithms, in that they both start with the quick algorithm, which has good

Introselect	
Class	Selection algorithm
Data structure	Array
Worst-case performance	O(<i>n</i>)
Best-case performance	O(<i>n</i>)

average performance and low overhead, but fall back to an optimal worst-case algorithm (with higher overhead) if the quick algorithm does not progress rapidly enough. Both algorithms were introduced by David Musser in (Musser 1997), with the purpose of providing generic algorithms for the C++ Standard Library that have both fast average performance and optimal worst-case performance, thus allowing the performance requirements to be tightened.^[1] However, in most C++ Standard Library implementations that use introselect, another "introselect" algorithm is used, which combines quickselect and heapselect, and has a worst-case running time of $O(n \log n)^{[2]}$.

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Answer. If the pivot is always the median, the array is always split into almost equallysized partitions. Therefore, the algorithm would run in $\Theta(n \log n)$.

Quicksort Improvement

What is the order of growth of the running time of **quicksort** is if a linear time median finding algorithm is used to pick the pivot?

Answer. If the pivot is always the median, the array is always split into almost equallysized partitions. Therefore, the algorithm would run in $\Theta(n \log n)$.

However: the overhead for finding the pivot would be high and the algorithm would be slower in practice compared to just picking the pivot randomly.

• Finding the largest (or smallest) element: n - 1 compares. Perform a linear scan in the array.

- Finding the largest (or smallest) element: *n* − 1 compares.
 Perform a linear scan in the array.
- Finding the largest and smallest elements:
 - 2n-3 compares.

Perform a linear scan to find the largest (n - 1) and then another scan on the elements (excluding the largest) to find the minimum (n - 2).

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We can use some of the information gained while finding the maximum to find the minimum!



 $\frac{3}{2}n-2$ compares

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Theorem. Any comparison-based algorithm for finding both the minimum and maximum elements in an arbitrary array must perform at least $\frac{3}{2}n - 2$ compares in the worst case*.

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Theorem. Any comparison-based algorithm for finding both the minimum and maximum elements in an arbitrary array must perform at least $\frac{3}{2}n - 2$ compares in the worst case^{*}.

- Finding the 2nd largest element:
 - 2n-3 compares.

Perform a linear scan to find the largest (n - 1) and then another scan on the elements (excluding the largest) to find the second largest (n - 2).

* for the **proof**, see Computer Algorithms: Introduction to Design and Analysis for Sara Baase and Allen Van Gelder

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A Tournament-based approach.

Observation. A key that loses to a key other than the max can't possibly be the second largest. There are at least two keys larger than that key: the max and the key it lost to!



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The second largest must be on this path! (must have lost to the max)

A Tournament-based approach.

Observation. Keys that lose to keys other than the max can't possibly be the second largest. Proof by contradiction.

Analysis. (assuming *n* is a power of 2)

• The algorithm performs $\frac{n}{2} + \frac{n}{4} + \frac{n}{8} + \dots + 1 = n - 1$ compares to find the max.



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Theorem. Any comparison-based algorithm for finding the second largest element in an arbitrary array must make at least $n + \lceil \log_2 n \rceil - 2$ compares in the worst case*.

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Implementation. How can we keep track of which elements lost to the max?

* for the **proof**, see Computer Algorithms: Introduction to Design and Analysis for Sara Baase and Allen Van Gelder

Use a heap-like structure to keep track of the comparisons.

1. Load the *n* elements into the right half of an array of size 2n - 1.



4 0 6 5 2 3 0

- 1. Load the *n* elements into the right half of an array of size 2*n*.
- 2. Compute the max of each pair and store it at the location of the parent.





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BUILD-HEAP(a[], n)

Create an array named h[] of size 2n-1Copy a[0 \rightarrow n-1] to h[n-1 \rightarrow 2n-2]

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Create an array named h[] of size 2n-1Copy a[0 \rightarrow n-1] to h[n-1 \rightarrow 2n-2] i = 2n-3 start at the 2nd to last element in the array



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```
Create an array named h[] of size 2n-1

Copy a[0 \rightarrow n-1] to h[n-1 \rightarrow 2n-2]

i = 2n-3

while (i > 0):

h[PARENT(i)] = max(h[i], h[i+1])

store the max at

the index of the

parent node

(i-1)/2
```



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i = i-2

move to the

next pair
```



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```

HEAP-FIND-MAX(h[], n)

```
max2 = a very small number, i=0
while i < n - 1:
    elements after this
    are leaves</pre>
```



BUILD-HEAP(a[], n)

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i = i-2
```

HEAP-FIND-MAX(h[], n)

```
max2 = a very small number, i=0
while i < n - 1:
    if (h[i] == h[LEFT(i)]):
        max2 = MAX(max2, h[RIGHT(i)])
        i = LEFT(i)
else:
        max2 = MAX(max2, h[LEFT(i)])
        i = RIGHT(i)</pre>
```

otherwise, compare the current 2nd largest to the left child and then move to the right child

BUILD-HEAP(a[], n)

```
Create an array named h[] of size 2n-1

Copy a[0 \rightarrow n-1] to h[n-1 \rightarrow 2n-2]

i = 2n-3

while (i > 0):

h[PARENT(i)] = max(h[i], h[i+1])

i = i-2
```

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return max2

optional

Assume that you receive an arbitrary stream of numbers. How can we efficiently report the median at any point in time?

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Solution 1. Maintain a max-heap:

insert(): $O(\log n)$

median(): $O(n \log n)$

Remove from the heap the first $\frac{n}{2}$ elements to reach the median and then insert them back.

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Solution 2. Maintain an unordered array:

insert(): $\Theta(1)$ Add to the end of the list. Note that the array might resize, so the running time is amortized.

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Solution 3. Maintain a sorted array:

insert(): O(n)Search for the right position and then shift any elements that come after.

median(): $\Theta(1)$ The median is always at index $\frac{n}{2}$.

Solution 4. Use a max-heap to store the lower half of the elements (\leq median) and a min-heap to store the upper half of the elements (> median).

Assume that the max-heap is named **left** and the min-heap is named **right**. Ensure that:

• Any element in **left** is smaller than or equal to all the elements in **right**.

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Example: [1 2 3 • 4 5 6] **Example**: [1 2 3 4 • 5 6 7]

General Idea:

- **Insert** the new element into the left heap if it is less than or equal to the current median and to the right if it is greater than the current median.
- **Rebalance** the heaps by moving an element from the larger heap to the smaller heap if the size invariant is violated.

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```
insert(k):
    If k <= left.max():left.insert(k)
    Else: right.insert(k)</pre>
```

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```
insert(k):
    remove the max from left
    and insert it into right
    If k <= left.max():left.insert(k)
    Flse:
        right.insert(k)
    If left.size() > right.size()+1: right.insert(left.delMax()).
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<pre>insert(k):</pre>	insert into the correct heap	
If k <= left. Else:	.max(): left. insert(k) right. insert(k)	rebalance the heaps if necessary
<pre>If left.size() > right.size()+1: right.insert(left.delMax()).</pre>		
If right. siz	e() > left.size(): lef	t. insert(right. delMin()).

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Example: [1 2 3 • 4 5 6] **Example**: [1 2 3 4 • 5 6 7]

Running Time:

insert(): $O(\log n)$ Inserting into the left or the right heaps is $O(\log n)$ and rebalancing is $O(\log n)$.

median(): $\Theta(1)$ The median is always left.max().