

Order Statistics

We often want to compute a **median** of a list of values.
(It gives a more accurate picture than the average sometimes.)

More generally, what element has position k in the sorted list?
(For example, for percentiles or trimmed means.)

Selection Problem

Given a list A of size n , and an integer k ,
what element is at position k in the sorted list?

Sorting-Based Solutions

- First idea: Sort, then look-up

- Second idea: Cut-off selection sort

Heap-Based Solutions

- First idea: Use a size- k max-heap

- Second idea: Use a size- n min-heap

Algorithm Design

What **algorithm design paradigms** could we use to attack the selection problem?

- Reduction to known problem
What we just did!
- Memoization/Dynamic Programming
Would need a recursive algorithm first...
- Divide and Conquer
Like binary search — seems promising. What's the problem?

A better “divide”

- Finding the element at a given position is tough.
- But find the *position* of a given element is easy!

Idea: Pick an element (the **pivot**), and sort around it.

```
partition(A)
```

Input: Array A of size n . **Pivot** is in $A[0]$.

Output: Index p such that $A[p]$ holds the pivot, and $A[a] \leq A[p] < A[b]$ for all $0 \leq a < p < b < n$.

```
1 i := 1
2 j := n - 1
3 while i <= j do
4   if A[i] <= A [0] then
5     i := i + 1
6   else if A[j] > A[0] then
7     j := j - 1
8   else
9     swap (A[i], A[j])
10 end while
11 swap (A[0], A[j])
12 return j
```

Analysis of partition

- **Loop Invariant:** Everything before $A[j]$ is \leq the pivot; everything after $A[j]$ is greater than the pivot.

- **Running time:** Consider the value of $j - i$.

Choosing a Pivot

The choice of pivot is really important!

- Want the partitions to be close to the same size.
- What would be the very best choice?

Initial (dumb) idea: Just pick the first element:

choosePivot1(A)

Input: Array A of length n

Output: Index of the pivot element we want

```
1 return 0
```

The Algorithm

quickSelect1(A,k)

Input: Array A of length n , and integer k

Output: Element at position k in the sorted array

```
1 swap (A[0], A[choosePivot1(A)])
2 p := partition(A)
3 if p = k then
4   return A[p]
5 else if p < k then
6   return quickSelect1(A[p+1..n-1], k-p-1)
7 else if p > k then
8   return quickSelect1(A[0..p-1], k)
```

QuickSelect: Initial Analysis

- Best case:

- Worst case:

Average-case analysis

Assume all $n!$ permutations are equally likely.
Average cost is sum of costs for all permutations, divided by $n!$.

Define $T(n, k)$ as average cost of `quickSelect1(A, k)`:

$$T(n, k) = n + \frac{1}{n} \left(\sum_{p=0}^{k-1} T(n-p-1, k-p-1) + \sum_{p=k+1}^{n-1} T(p, k) \right)$$

See the book for a precise analysis, or ...

Average-Case of `quickSelect1`

First simplification: define $T(n) = \max_k T(n, k)$

The key to the cost is the **position of the pivot**.

There are n possibilities, but can be grouped into:

- **Good pivots:** The position p is between $n/4$ and $3n/4$.
Size of recursive call:
- **Bad pivots:** Position p is less than $n/4$ or greater than $3n/4$
Size of recursive call:

Each possibility occurs $\frac{1}{2}$ of the time.

Average-Case of quickSelect1

Based on the cost and the probability of each possibility, we have:

$$T(n) \leq n + \frac{1}{2}T\left(\frac{3n}{4}\right) + \frac{1}{2}T(n)$$

(Assumption: every permutation in each partition is also equally likely.)

Drawbacks of Average-Case Analysis

To get the average-case we had to make some BIG assumptions:

- Every permutation of the input is equally likely
- Every permutation of each half of the partition is still equally likely

The first assumption is actually false in most applications!

Randomized algorithms

Randomized algorithms use a source of **random numbers** in addition to the given input.

AMAZINGLY, this makes some things faster!

Idea: Shift assumptions on the *input distribution* to assumptions on the *random number distribution*.
(Why is this better?)

Specifically, assume the function `random(n)` returns an integer between 0 and n-1 with uniform probability.

Randomized quickSelect

We could shuffle the whole array into a randomized ordering, or:

- 1 Choose the pivot element randomly:

choosePivot2(A)

```
1 return random(n)
```

- 2 Incorporate this into the quickSelect algorithm:

quickSelect2(A)

```
1 swap (A[0], A[choosePivot2(A)])  
2 ...
```

Analysis of quickSelect2

The **expected cost** of a randomized algorithm is the probability of each possibility, times the cost given that possibility.

We will focus on the **expected worst-case running time**.

Two cases: good pivot or bad pivot. Each occurs half of the time. . .
The analysis is exactly the same as the average case!

Expected worst-case cost of quickSelect2 is $\Theta(n)$.
Why is this better than average-case?

Do we need randomization?

Can we do selection in linear time **without randomization**?

Blum, Floyd, Pratt, Rivest, and Tarjan figured it out in 1973.

But it's going to get a little complicated. . .

Median of Medians

Idea: Develop a divide-and-conquer algorithm for choosing the pivot.

- ① Split the input into m sub-arrays
- ② Find the median of each sub-array
- ③ Look at just the m medians, and take the median of those
- ④ Use the median of medians as the pivot

This algorithm will be **mutually recursive** with the selection algorithm.
Crazy!

Note:

- q is a parameter, not part of the input. We'll figure it out next.
- `quickSelect3(A,k)` finds the element at position k in the sorted array and re-arranges A so that $A[k]$ is that element.

`choosePivot3(A)`

```
1 m := floor(n/q)
2 for i from 0 to m-1 do
3   // Find median of next group, move to front
4   quickSelect3(A[i*q..(i+1)*q-1], floor(q/2))
5   swap(A[i], A[i*q + floor(q/2)])
6 end for
7 // Find the median of medians
8 quickSelect3(A[0..m-1], floor(m/2))
9 return floor(m/2)
```

Worst case of `choosePivot3(A)`

Assume all array elements are distinct.

Question: How unbalanced can the pivoting be?

- Chosen pivot *must* be greater than $\lfloor m/2 \rfloor$ medians.
- Each median must be greater than $\lfloor q/2 \rfloor$ elements.
- Since $m = \lfloor n/q \rfloor$, the pivot must be greater than (and less than) approximately

$$\left\lfloor \frac{n}{2q} \right\rfloor \cdot \left\lfloor \frac{q}{2} \right\rfloor$$

elements in the worst case.

Worst-case example, $q = 3$

$A = [13, 25, 18, 76, 39, 51, 53, 41, 96, 5, 19, 72, 20, 63, 11]$

Aside: “At Least Linear”

Definition

A function $f(n)$ is **at least linear** if and only if $f(n)/n$ is non-decreasing (for sufficiently large n).

- Any function that is $\Theta(n^c(\log n)^d)$ with $c \geq 1$ is “at least linear”.
- You can pretty much assume that any running time that is $\Omega(n)$ is “at least linear”.
- **Important consequence:** If $T(n)$ is at least linear, then $T(m) + T(n) \leq T(m+n)$ for any positive-valued variables n and m .

Analysis of quickSelect3

Since quickSelect3 and choosePivot3 are **mutually recursive**, we have to analyze them together.

- Let $T(n) =$ worst-case cost of quickSelect3(A,k)
- Let $S(n) =$ worst-case cost of selectPivot3(A)
- $T(n) =$
- $S(n) =$
- Combining these, $T(n) =$

Choosing q

- What if q is big? Try $q = n/3$.

- What if q is small? Try $q = 3$.

Choosing q

What about $q = 5$?

QuickSort

QuickSelect is based on a sorting method developed by Hoare in 1960:

`quickSort1(A)`

Input: Array A of size n

Output: The array is sorted in-place.

```
1  if  $n > 1$  then
2      swap (A[0], A[choosePivot1(A)])
3      p := partition(A)
4      quickSort1(A[0..p-1])
5      quickSort1(A[p+1..n-1])
6  end if
```

QuickSort vs QuickSelect

- Again, there will be three versions depending on how the pivots are chosen.
- Crucial difference: QuickSort makes **two** recursive calls
- Best-case analysis:
- Worst-case analysis:
- We could ensure the best case by using quickSelect3 for the pivoting.
In practice, this is **too slow**.

Average-case analysis of quickSort1

Of all $n!$ permutations, $(n-1)!$ have pivot $A[0]$ at a given position i .

Average cost over all permutations:

$$T(n) = \frac{1}{n} \sum_{i=0}^{n-1} (T(i) + T(n-i-1)) + \Theta(n), \quad n \geq 2$$

Do you want to solve this directly?

Instead, consider the **average depth** of the recursion.
Since the cost at each level is $\Theta(n)$, this is all we need.

Average depth of recursion for quickSort1

$D(n)$ = average recursion depth for size- n inputs.

$$H(n) = \begin{cases} 0, & n \leq 1 \\ 1 + \frac{1}{n} \sum_{i=0}^{n-1} \max(H(i), H(n-i-1)), & n \geq 2 \end{cases}$$

- We will get a **good pivot** ($n/4 \leq p \leq 3n/4$) with probability $\frac{1}{2}$
- The *larger* recursive call will determine the height (i.e., be the “max”) with probability at least $\frac{1}{2}$.

Summary of QuickSort analysis

- quickSort1: Choose $A[0]$ as the pivot.
 - ▶ Worst-case: $\Theta(n^2)$
 - ▶ Average case: $\Theta(n \log n)$
- quickSort2: Choose the pivot randomly.
 - ▶ Worst-case: $\Theta(n^2)$
 - ▶ **Expected** case: $\Theta(n \log n)$
- quickSort3: Use the median of medians to choose pivots.
 - ▶ Worst-case: $\Theta(n \log n)$

Sorting so far

We have seen:

- Quadratic-time algorithms:
BubbleSort, SelectionSort, InsertionSort
- $n \log n$ -time algorithms:
HeapSort, MergeSort, QuickSort

$O(n \log n)$ is **asymptotically optimal** in the comparison model.

So how could we do better?

BucketSort

BucketSort is a general approach, not a specific algorithm:

- ① Split the range of outputs into k groups or **buckets**
- ② Go through the array, put each element into its bucket
- ③ Sort the elements in each bucket (perhaps recursively)
- ④ Dump sorted buckets out, in order

Notice: No comparisons!

countingSort(A,k)

Input: Integer array A of length n , and integer k such that every $A[i]$ satisfies $0 \leq A[i] < k$.

Output: A gets sorted.

```
1 C := new array of size k
2 for i from 0 to k do
3   C[i] := 0
4 for i from 0 to n-1 do
5   C[A[i]] := C[A[i]] + 1
6 for i from 1 to k-1 do
7   C[i] := C[i] + C[i-1]
8 B := copy(A)
9 for i from n-1 down to 0 do
10  C[B[i]] := C[B[i]] - 1
11  A[C[B[i]]] := B[i]
12 end for
```

Analysis of CountingSort

- Time:

- Space:

Stable Sorting

Definition

A sorting algorithm is **stable** if elements with the same key stay in the same order.

- Quadratic algorithms and MergeSort are easily made stable
- QuickSort will require extra space to do **stable partition**.
- CountingSort is stable.

radixSort(A,d,B)

Input: Integer array A of length n , and integer d and k such that every $A[i]$ has d digits $A[i] = x_{d-1}x_{d-2} \cdots x_0$, to the base B .

Output: A gets sorted.

```
1 for i from 0 to d-1 do
2   // Sort by the  $x_i$ 's
3   countingSort(A,B) by every  $x_i$ 
```

Works because CountingSort is stable!

Analysis:

Summary of Sorting Algorithms

Every algorithm has its place and purpose!

Algorithm	Analysis	In-place?	Stable?
SelectionSort	$\Theta(n^2)$ best and worst	yes	yes
InsertionSort	$\Theta(n)$ best, $\Theta(n^2)$ worst	yes	yes
HeapSort	$\Theta(n \log n)$ best and worst	yes	no
MergeSort	$\Theta(n \log n)$ best and worst	no	yes
QuickSort	$\Theta(n \log n)$ best, $\Theta(n^2)$ worst	yes	no
CountingSort	$\Theta(n + k)$ best and worst	no	yes
RadixSort	$\Theta(d(n + k))$ best and worst	yes	yes

Unit 5 Summary

- Selection problem
- Partition
- quickSelect and quickSort
- Average-case analysis
- Randomized algorithms and analysis
- Median of medians
- Non-comparison based sorting
- BucketSort, CountingSort, RadixSort
- Stable sorting