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”

Consider this array: $A = [60, 43, 61, 87, 89, 87, 77, 11, 49, 45]$

- Difficult: Finding the element at a given position.
  For example, what is the 5th-smallest element in $A$?

- Easier: Finding the position of a given element.
  For example, what is the position of $x = 77$ in the sorted order?

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

Partition Algorithm

**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 $0 \leq a < p < b < n$.

```python
def partition(A):
    n = len(A)
    i, j = 1, n-1
    while i <= j:
        if A[i] <= A[0]:
            i = i + 1
        elif A[j] > A[0]:
            j = j - 1
        else:
            swap(A, i, j)
    swap(A, 0, j)
    return j
```
QuickSelect

Analysis of partition

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

- **Running time**: Consider the value of \( j - i \).

QuickSelect

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:

**Input**: Array \( A \) of length \( n \)

**Output**: Index of the pivot element we want

```python
def choosePivot1(A):
    return 0
```

QuickSelect

The Algorithm

**Input**: Array \( A \) of length \( n \), and integer \( k \)

**Output**: Element at position \( k \) in the sorted array

```python
def quickSelect1(A, k):
    n = len(A)
    swap(A, 0, choosePivot1(A))
    p = partition(A)
    if p == k:
        return A[p]
    elif p < k:
        return quickSelect1(A[p+1 : n], k-p -1)
    elif p > k:
        return quickSelect1(A[0 : p], 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.
Analysis of QuickSelect

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.)

Randomized Pivot Choosing

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 \( \text{random}(n) \) returns an integer between 0 and \( n-1 \) with uniform probability.
Randomized Pivot Choosing

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

1. Choose the pivot element randomly:

Randomized pivot choice

```python
def choosePivot2(A):
    # This returns a random number from 0 up to n-1
    return randrange(0, len(A))
```

2. Incorporate this into the quickSelect algorithm:

Randomized selection

```python
def quickSelect2(A, k):
    swap(A, 0, choosePivot2(A))
    # ... the rest is the same as quickSelect1
```

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?

Median of Medians

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.

```python
def choosePivot3(A):
    n = len(A)
    m = n // q

    # base case
    if m <= 1:
        return n // 2

    # Find median of each size-\( q \) group
    medians = []
    for i in range(0, m):
        medians.append(quickSelect3(A[i*q : (i+1)*q], q//2))

    # Find median of medians
    quickSelect3(medians, m//2)
    return m//2
```

---

**Worst case of choosePivot3(A)**

Assume all array elements are distinct.

**Question:** How unbalanced can the pivoting be?

- At least \( \lceil m/2 \rceil \) medians must be \( \leq \) the chosen pivot.
- At least \( \lceil q/2 \rceil \) elements are \( \leq \) each median.
- So the pivot must be greater than or equal to at least

\[
\frac{m}{2}, \frac{q}{2}
\]

... elements in the array, in the worst case.

- By the same reasoning, as many elements must be \( \geq \) the chosen pivot.
Worst-case example, $q = 3$


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 \( q = \frac{n}{3} \).

- What if \( q \) is small? Try \( q = 3 \).

---

**QuickSort**

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

```python
def quickSort1(A):
    n = len(A)
    if n > 1:
        swap(A, 0, choosePivot1(A))
        p = partition(A)
        A[0 : p] = quickSort1(A[0 : p])
    return A
```
QuickSort

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

$$D(n) = \text{average recursion depth for size-}n \text{ inputs.}$$

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

- 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 $\frac{1}{2}$.
QuickSort

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 without Comparisons

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:

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

Notice: No comparisons!
countingSort(A, k)

**Precondition** $0 \leq A[i] < k$ for all indices $i$

def countingSort(A, k):
    C = [0] * k  # size-k array filled with 0's
    for x in A:
        C[x] = C[x] + 1
    # Now C has the counts.
    # P will hold the positions.
    P = [0]
    for i in range(1, k):
        P.append(P[i-1] + C[i-1])
    # Now copy everything into its proper position.
    for x in copy(A):
        A[P[x]] = x
        P[x] = P[x] + 1
    return A

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 integers d and B such that every
A[i] has d digits A[i] = x_{d-1}x_{d-2}...x_0, to the base B.

**Output:** A gets sorted.

```python
def radixSort(A, d, B):
    for i in range(0, d):
        countingSort(A, B)  # based on the i'th digits
    return A
```

Works because CountingSort is stable!

**Analysis:**

### Summary of Sorting Algorithms

Every algorithm has its place and purpose!

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Analysis</th>
<th>In-place?</th>
<th>Stable?</th>
</tr>
</thead>
<tbody>
<tr>
<td>SelectionSort</td>
<td>Θ(n^2) best and worst</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>InsertionSort</td>
<td>Θ(n) best, Θ(n^2) worst</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>HeapSort</td>
<td>Θ(n log n) best and worst</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>MergeSort</td>
<td>Θ(n log n) best and worst</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>QuickSort</td>
<td>Θ(n log n) best, Θ(n^2) worst</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>CountingSort</td>
<td>Θ(n + k) best and worst</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>RadixSort</td>
<td>Θ(d(n + k)) best and worst</td>
<td>yes</td>
<td>yes</td>
</tr>
</tbody>
</table>

### Back to Kruskal’s

Remember Kruskal’s algorithm for finding MSTs?

Two major components:
- Sorting the edges by weight
- Doing a bunch of union and find operations

We’re ready to optimize it now!
More MSTs

Union-Find with Path Compression

Idea: Each set is stored as a **tree**, not a linked list.

Final analysis of Kruskal's