06. Linear-Time Sorting and Selection

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Big Idea in Computer Science

"What is old is new again": CS principles are solved science; society's needs, economic factors, and fads dictate which are prominent and which are in the background

- thin clients dominated the mainframe era; thick clients dominated the PC era; thin clients dominate the web app era
- memory conservation was critical prior to the 90s; programmer labor was more important, until mobile phones
- Unix rose (70s), fell (80s-90s), rose again (MacOS, iOS, Android, ChromeOS, Linux, PlayStation, embedded)
- algorithms were considered ivory-tower theory until recently

Protip: the CS material that seems irrelevant now, will probably become extremely marketable later in your career

Big Idea in Algorithm Design

Paramaterized complexity: algorithm complexity measured both in terms of input size n, **and** some parameter describing the values in the input

- machine word size W (e.g. $W = 64$ on modern PCs)
- $\#$ distinct values k

Pseudopolynomial: polynomial over both n, and also parameters

- radix sort takes $\Theta(nW)$ time
- strictly speaking W could be as large as n, so $\Theta(nW) = \Theta(n^2)$, unimpressive
- in practice all real-world computers have $W \in \Theta(1)$ so $\Theta(nW) = \Theta(n)$, faster than $\Theta(n \log n)$
- arguably defying the spirit of the Random Access Model

Tool to circumvent lower bounds, *NP*-hardness

The Lower Bound for the Sorting Problem

Recall the precise phrasing of the theorem:
Any comparison sort algorithm requires $\Omega(n \log n)$ *comparisons in the worst case.*

Bad news: $O(n \log n)$ “speed limit” for this important problem

Good news:

- optimal $\Theta(n \log n)$-time algorithms: mergesort, heapsort, quicksort
- loophole: theorem only applies to “comparison sorts”
- loophole: theorem applies to the general sorting problem, but we could make the problem more specific

Counting Sort Problem

Recall the classical *sorting problem:*
input: a sequence of n numbers $A = \langle a_1, a_2, \ldots, a_n \rangle$
output: a permutation (reordering) $\langle a'_1, a'_2, \ldots, a'_n \rangle$ of the input sequence such that $a'_1 \leq a'_2 \leq \ldots, a'_n$.

What if the inputs a_i are all bounded integers?

counting sort problem: (changes are $\underline{\text{underlined}}$)
input: $\underline{\text{an integer } k \geq 0 \text{, and}}$ a sequence of n $\underline{\text{integers}}$
$A = \langle a_1, a_2, \ldots, a_n \rangle$, $\underline{\text{where each } a_i \in [0, k]}$
output: same

Turns out this change admits a $\Theta(n)$-time algorithm.

Counting Sort Idea

- each a_i can work as an array index
- count the number of occurrences of each value; create array C where

$$C[x] = \text{ the number of times that } x \text{ appears in A}$$

- let B be the output array
- use the counts in C to plan out which indices of B will hold each a_i
- fill in B using this information

Counting Sort Pseudocode

```
function COUNTING-SORT(A, B, k)
    allocate new array $C[0, \ldots, k]$, initialized to all zeroes
    for $j$ from 1 to $A.length$ do
        $C[A[j]]++$            ▷ $C[i]$ is the number of elements $= i$
    end for
    for $i$ from 1 to $k$ do
        $C[i] += C[i-1]$       ▷ $C[i]$ is the number of elements $\leq i$
    end for
    for $j$ from $A.length$ down to 1 do
        $B[C[A[j]]] = A[j]$
        $C[A[j]]--$
    end for
end function
```

Counting Sort Analysis

- allocate C: $\Theta(k)$ time
- first **for** loop: $\Theta(n)$ time
- second **for** loop: $\Theta(k)$ time
- third **for** loop: $\Theta(n)$ time
- total $= \Theta(k + n + k + n) = \Theta(2k + 2n) = \Theta(k + n)$ time

When Counting Sort Wins

If $k \in O(n)$, then counting sort takes $\Theta(k+n) = \Theta((n)+n) = \Theta(n)$ time.

Applications where $k \ll n$

- DNA sequences have only $k = 4$ bases A, C, G, T; human genome has $n \approx 3$ billion bases
- n-character ASCII string has only $k = 127$ character values
- log of website analytics has n hits but only k distinct web page URLs; each page is visited many times so $n \gg k$

When Counting Sort Loses

In the general sorting problem, each a_i is unbounded, so the maximum element could use $\Theta(n)$ bits, have value

$$a_i = 2^n = k$$

and force counting sort to take

$$\Theta(k + n) = \Theta((2^n) + n) = \Theta(2^n)$$

time, which is **exponential** in n and much more expensive than $\Theta(n \log n)$

$\implies$ counting sort is optimal when the software designer knows that the input is always a set of k integers with $k \in O(n)$

$\implies$ **but** if that is not guaranteed, comparison sorts are still optimal

Stable Sorting

stable sorting algorithm: does not swap order of ties

if $a_i = a_j$ and $i < j$ then $i' < j'$

Ex.: suppose we sort

$$[(47, a), (13, c), (28, b), (13, d)]$$

by the first element of each pair; a *stable* sort guarantees $(13, c)$ comes before $(13, d)$

Stability is a convenient, desirable property

Stable: insertion sort, mergesort, counting sort
Not stable: heapsort, quicksort

“Radix”

Vocabulary quiz:

- what does **radix** mean?
- where else do we use the word “radix”?

Radix Sort Overview

- make counting sort more robust to large elements
- sort one digit at a time
- i.e. sort by least-significant-digit, then by second-least-significant-digit, . . ., sort by most-significant digit
- e.g. to sort names in a spreadsheet: sort by first name, then by last name
- originally used by pre-digital punchcard sorting machines (what's old...)
- now used for parallel sort in GPU (...is new again)

Radix Sort Worked Example

(Sorting one base-10 digit at a time.)

7	7	5
0	5	3
7	6	2
7	9	1
6	7	4
5	2	1
3	3	4
2	2	5

7	9	1
5	2	1
7	6	2
0	5	3
6	7	4
3	3	4
7	7	5
2	2	5

5	2	1
2	2	5
3	3	4
0	5	3
7	6	2
6	7	4
7	7	5
7	9	1

0	5	3
2	2	5
3	3	4
5	2	1
6	7	4
7	6	2
7	7	5
7	9	1

Radix Sort, 1 bit at a time

```
function RADIX-SORT-1(A, W)
    for $i$ from 1 to $W$ do
        use a stable sort to sort $A$ based only on bit position $i$
    end for
end function
```

Using counting sort as the stable sort, we have $k = 2$ (bit values 0 or 1) so each loop iteration takes $\Theta(k + n) = \Theta(2 + n) = \Theta(n)$ time

Clearly W iterations $\implies \Theta(nW)$ total time

Radix Sort, 8 bits at a time

```
function RADIX-SORT-8(A, W)
    for $i$ from 1 to $\lceil W/8 \rceil$ do
        stably sort $A$ on bits $8i - 7$ through $8i$
    end for
end function
```

$k = 2^8 = 256 \in \Theta(1)$
number of iterations is $\lceil nW/8 \rceil \in \Theta(n)$
$\implies$ still $\Theta(nW)$ time, but with different constant factors

Let r =#bits per pass; optimal choice of r minimizes

$$\lceil W/r \rceil \cdot (2^r + n)$$

Minimum and Maximum

```
function MINIMUM(A)
    min = A[1]
    for $i$ from 2 to $A.length$ do
        if $min > A[i]$ then
            $min = A[i]$
        end if
    end for
    return $min$
end function
```

$\Theta(n)$ time

can also find maximum in $\Theta(n)$ time, or both in $\Theta(n)$ time

Selection Problem and Baseline Algorithm

input: array of n numbers $A = \langle a_1, a_2, \ldots, a_n \rangle$; index $i \in \{1, 2, \ldots, n\}$
output: the ith smallest element of A

```
function SELECTION-BY-SORTING(A, i)
    return $MERGE - SORT(A)[i]$
end function
```

Clearly $\Theta(n \log n)$ time

Surprise: selection can be solved in only $\Theta(n)$ time

Randomized Quicksort Review

```
function RQSORT(A, p, r)
    if $p < r$ then
        $q = RPART(A, p, r)$
        $RQSORT(A, p, q-1)$
        $RQSORT(a, q+1, r)$
    end if
end function
```

Non-stable sort in $\Theta(n \log n)$ expected time but $\Theta(n^2)$ worst-case time

```
function RPART(A, p, r)
    $i$ = random in $[p, r]$
    $swap(A[i], A[r])$
    $pivot = A[r]$
    $i = p$
    for $j$ from $p$ to $r-1$ do
        if $A[j] < pivot$ then
            $swap(A[i], A[j])$
            $i++$
        end if
    end for
    $swap(A[i], A[r])$
    return $i$
end function
```

Randomized Selection Overview

- combining ideas from binary search and quicksort
- recursively search for ith smallest element
- do randomized partition; then
- three cases
  - pivot happens to be ith smallest
  - need to keep searching before pivot
  - need to keep searching after pivot
- expected runtime is $T(n) \approx T(n/2) + \Theta(n)$
- counterintuitively, that solves to $\Theta(n)$

Randomized Selection Pseudocode

```
function RSELECT(A, p, r, i)
    if $p == r$ then
        return $A[p]$                          ▷ base case, done
    end if
    $q = RPART(A, p, r)$                       ▷ partition, $q$ is pivot index
    $k = q - p + 1$                            ▷ $k$ = number of elements before pivot
    if $i == k$ then
        return $A[q]$                          ▷ pivot is answer
    else if $i < k$ then
        return $RSELECT(A, p, q - 1, i)$
    else
        return $RSELECT(A, q + 1, r, i - k)$   ▷ $i$ decreases by $k$
    end if
end function
```

Randomized Selection Analysis

- at most one recursive call, on $n/2$ elements on average
- partitioning takes $\Theta(n)$ time
- rest of algorithm takes $\Theta(1)$ time
- expected running time

  $$T(n) = T(n/2) + \Theta(n)$$

  which is only $\Theta(n)$ by master theorem
- worst case is the same for quicksort, extreme pivot at each step, $\Theta(n^2)$ time
- **takeaway:** randomized selection takes $\Theta(n)$ expected time and $\Theta(n^2)$ worst-case time

Deterministic Selection Overview

- **deterministic:** perfectly predictable; not randomized
- recall that $T(n) = T(fn) + \Theta(n)$ is $\Theta(n)$ for any fraction $0 < f < 1$, not just $f = 1/2$
- need: deterministic process to find a not-terrible pivot
- i.e. need at least fn elements on each side of the pivot, so that the worst-case recursive call is $T((1-f)n)$
- e.g. need at least $\frac{1}{3}n$ elements on each side of the pivot, so that there is a $T(\frac{1}{3}n)$ or $T(\frac{2}{3}n)$ call; worst-case is $T(\frac{2}{3}n)$; so

$$T(n) = T(\frac{2}{3}n) + \Theta(n)$$

which is still $\Theta(n)$ (though with worse constants)

Deterministic Selection Process

1. divide n elements into $\approx n/5$ groups of 5 elements each
2. find the median of each group with $SELECTION - BY - SORTING$; $\Theta(n(5\log 5)) = \Theta(n)$ time
3. form a new array of the medians, and recursively select the median of this array = "median-of-medians"; $T(n/5)$ time
4. partition as usual, using median-of-medians as the pivot; $\Theta(n)$ time
5. same three cases: either pivot is answer, or recurse before pivot, or recurse after pivot;
   T(max. # elements on either side of pivot)

Deterministic Selection Analysis

- let x be the median-of-medians; count elements $\geq x$
- suppose W.L.O.G. that input elements are distinct
- $\therefore$ at least half of the group-medians are $\geq x$
- $\therefore$ at least half of the groups contain at least 3 elements $\geq x$ each; except for the group containing x, and possibly one group with < 5 elements
- $\therefore$ #elements $\geq x$ is at least

$$3\left(\left\lceil \frac{1}{2}\left\lceil \frac{n}{5} \right\rceil \right\rceil - 2\right) \geq \frac{3}{10}n - 6$$

- symmetrically there are at least $\frac{3}{10}n - 6$ elements $\leq x$
- $\therefore$ recursively select at most $n - (\frac{3}{10}n - 6) = \frac{7}{10}n + 6$ elements

Deterministic Selection Analysis (continued)

For some $t \in \Theta(1)$,

$$T(n) \leq \begin{cases} O(1) & n < t \\ T(\lceil n/5 \rceil) + T(\frac{7}{10}n + 6) + O(n) & n \geq t. \end{cases}$$

The master theorem does not apply, but the substitution method can be used to show $T(n) \in O(n)$.

Takeaway: Deterministic selection takes $O(n)$ worst-case time.

Surprise: selection can be **derandomized** from $O(n)$ expected time to $O(n)$ worst-case time with no asymptotic overhead.

Impractical; much worse constant factors, not usually worth it.