

Chapter 8: Sorting in Linear Time

Lower Bound for Sorting

This section is **OPTIONAL**. The main take-away is that all comparison based sorting algorithms have a lower bound running time $\Omega(n \log n)$ for the worst-case.

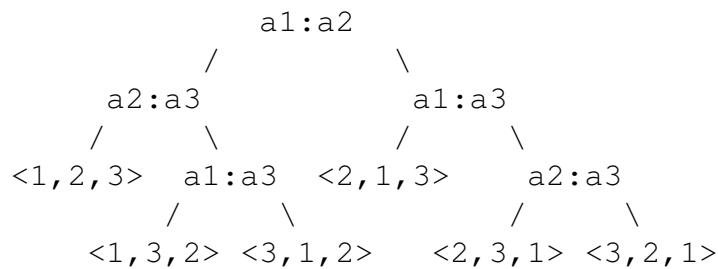
Comparison sort: A sorting algorithm that is based only on comparisons between the input elements.

Comparison sorts can be viewed abstractly in terms of decision trees.

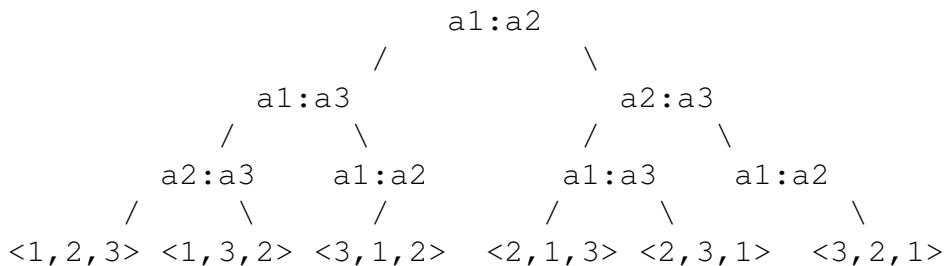
Decision trees: Given an input sequence $\langle a_1, a_2, \dots, a_n \rangle$,

- Each internal node is denoted by $a_i : a_j$, for $1 \leq i, j \leq n$.
- Each leaf node is denoted by a permutation $\langle \pi(1), \pi(2), \dots, \pi(n) \rangle$.
- Each path from the root to a leaf corresponds to an execution of the sorting algorithm for a specific input.
- The left branch of an internal node means $a_i \leq a_j$.
The right branch for an internal node means $a_i > a_j$.
- There are $n!$ permutations for n elements \implies there are at least $n!$ leaf nodes.

Ex: The decision tree for insertion sort with 3 elements.



Ex: The decision tree for selection sort with 3 elements.



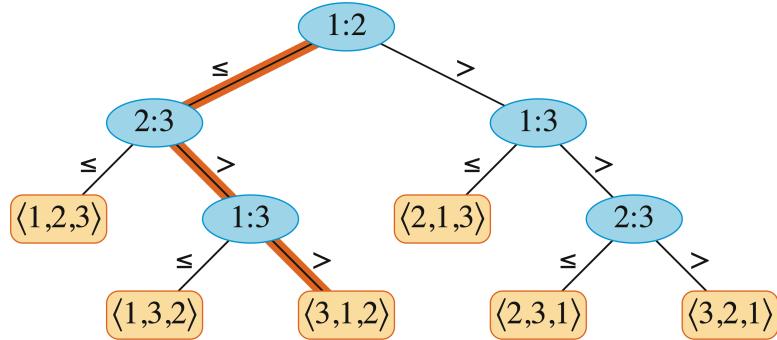
There are $n!$ permutations for n elements \Rightarrow the tree has at least $n!$ leaves.

Let h be the height of the tree \Rightarrow the tree has no more than 2^h leaves.

Thus,

$$n! \leq 2^h \Rightarrow h \geq \log(n!) \Rightarrow h = \Omega(n \log n)$$

The height of a decision tree means the number of comparisons for sorting in the worst-case.



\Rightarrow All comparison sorts have a lower bound running time $\Omega(n \log n)$ for the worst-case.

\Rightarrow It is impossible to find a new comparison based sorting algorithm that is asymptotically better than merge sort.

However, some non-comparison based sorting algorithms may run in linear time.

Counting Sort

Counting sort assumes that each of the n input elements is an integer within a range $[0..k]$, for some integer k .

An input array $A[1 : n]$, an output array $B[1 : n]$, and a temporary working storage $C[0 : k]$ are necessary for this algorithm. Thus, counting sort does not sort in place.

During the execution of counting sort, $C[i]$ maintains the # of elements less than or equal to i . For each element j in A , we put it into B at position $C[j]$.

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COUNTING-SORT (A, n, k)
1. let B[1:n] and C[0:k] be new arrays
2. for i = 0 to k
3.   C[i] = 0
4. for j = 1 to n
5.   C[A[j]] = C[A[j]] + 1
6. // C[i] contains the # of elements that is equal to i
7. for i = 1 to k
8.   C[i] = C[i] + C[i-1]
9. // C[i] now contains the # of elements less than or equal to i
10. // Copy A to B, starting from the end of A
11. for j = n downto 1
12.   B[C[A[j]]] = A[j]
13.   C[A[j]] = C[A[j]] - 1 // to handle duplicate values

```

Ex:

	1	2	3	4	5	6	7	8
A	2	5	3	0	2	3	0	3
	0	1	2	3	4	5		
C	2	0	2	3	0	1		

(a)

	0	1	2	3	4	5
C	2	2	4	7	7	8

(b)

	1	2	3	4	5	6	7	8
B							3	
	0	1	2	3	4	5		
C	2	2	4	6	7	8		

(c)

	1	2	3	4	5	6	7	8
B		0					3	
	0	1	2	3	4	5		
C	1	2	4	6	7	8		

(d)

	1	2	3	4	5	6	7	8
B		0				3	3	
	0	1	2	3	4	5		
C	1	2	4	5	7	8		

(e)

	1	2	3	4	5	6	7	8
B	0	0	2	2	3	3	3	5
	0	0	2	2	3	3	3	5
C	0	0	2	2	3	3	3	5

(f)

- Running time analysis:

Counting-Sort's running time is $\Theta(n+k)$.

If $k = O(n)$, then $\Theta(n+k) = \Theta(n)$. It's a linear time!

- Counting sort is a **stable** sorting algorithm: elements with the same value in the output array should be in the same order as they do in the input array.

- Insertion Sort: stable (if no “=” sign in comparison)
- Selection Sort: stable (if no “=” sign in comparison)
- Merge Sort: stable (if the “=” sign is in the comparison)
- Heap Sort: not stable (exchange $A[1] \rightarrow A[n]$)
- Quick Sort: not stable.

Ex: input: $< 5, 5', 5'', 3, 4 >$ and the output is $< 3, 4, 5'', 5, 5' >$.

Radix Sort

The Radix-Sort sorts by the least significant digit first, then by the 2nd least significant digit,

The sorting algorithm used to sort each digit should be stable; otherwise Radix-Sort will not work.

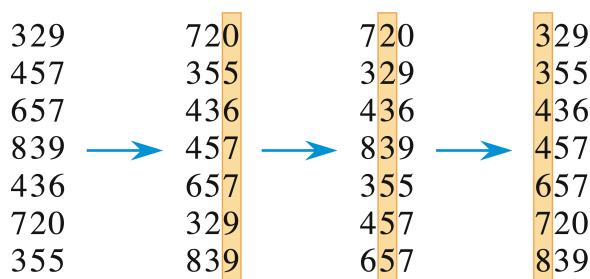
Ex:

213	321	312	123
312	312	212	132
123	212	213	212
212	stable	132	stable
321	----->	213	----->
132		123	312
^	^	^	^

Ex:

213	321	312	123
312	312	213 <-	132
123	212	212 <-	213 <-
212	stable	132 not stable	321 stable
321	----->	213 ----->	212 <-
132	123	123 ----->	312
^	^	^	^

Another example:



RADIX-SORT (A, d)

1. for i = 1 to d
2. use a stable sort to sort array A[1:n] on digit i

Two questions:

- Why does the algorithm need to use a stable sort to sort each digit?
- Why does the sorting start from sorting the least significant digit first?

Running time analysis: Suppose all n numbers have d or less digits.

If we use Counting-Sort as the sorting algorithm to sort each digit, then the running time for Radix-Sort is $d \cdot \Theta(n + k) = \Theta(dn + dk)$

If $k = O(n)$ and d is a constant, then the running time becomes $\Theta(n)$.

It's a linear time!

Recommended Exercise: Show how to sort n integers in the range 0 to $n^2 - 1$ in $O(n)$ time.

Solution:

We will assume that each digit has value in the range $0..n - 1$, that is $k = n$. That is, as if the numbers are written in radix- n or base- n (instead of the usual base 2 or base 10).

Counting sort now requires $O(n + k) = O(n)$ time.

Then each number will have two digits, so $d = 2$ as the range of the numbers is $[0..n^2 - 1]$.

Since $d = 2$, radix-sort requires two passes of Counting sort that each take $O(n)$ time. This the total run-time for radix-sort for this type of input is $O(n)$.

Bucket sort

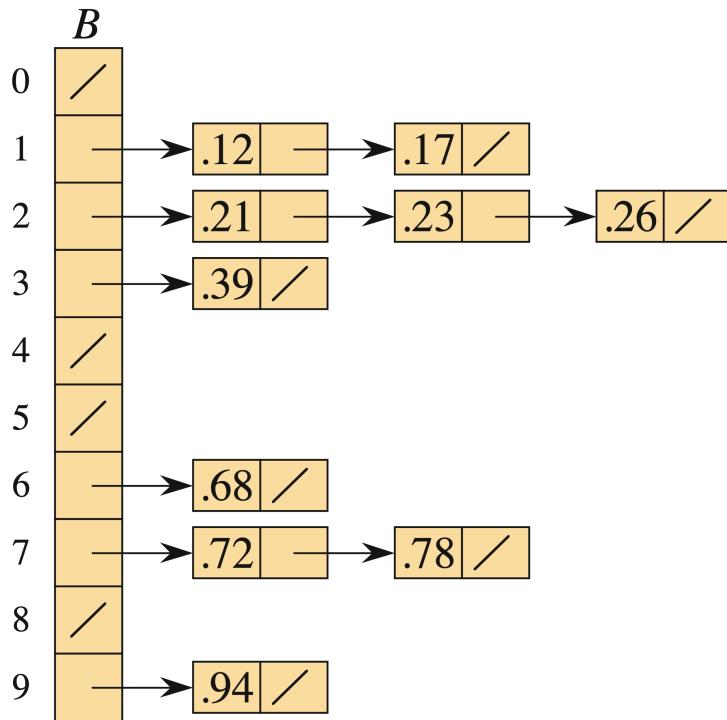
Assumption: input is drawn from the range $[0..1)$ with a uniform probability distribution.

Average case is $O(n)$.

```
BUCKET-SORT (A, n)
1. let B[0:n-1] be a new array
2. for i = 0 to n - 1
3.     make B[i] an empty list
4. for i = 1 to n
5.     insert A[i] into list B[floor(n A[i])]
6. for i = 0 to n - 1
7.     sort B[i] using insertion sort
8. concatenate the lists B[0], B[1], ..., B[n-1] together in order
9. return the concatenated lists
```

	<i>A</i>
1	.78
2	.17
3	.39
4	.26
5	.72
6	.94
7	.21
8	.12
9	.23
10	.68

(a)



(b)

If each list is of size $O(1)$, then the run-time is $O(n)$. The average case analysis requires advanced math so we will skip it here.

Notes: If the key values are distributed a known probability distribution, we can still get $O(n)$ average case. How can we take advantage of knowing the probability distribution to get all buckets to be of size $O(1)$ on the average?