

8. Average-Case Analysis of Algorithms + Randomized Algorithms

- 1) Probability tools you've seen allow formal definition of "average case" running time of algorithms
- 2) Coupled with a few analysis tricks you'll see in more detail in 421 or elsewhere, you can analyze those algorithms, and
- 3) Adding randomness to *algorithms* can have surprising benefits, and again, you've got the basic tools needed to understand the issues and do the necessary analysis
- 4) Specifics: "average" case analysis of insertion sort and quicksort, and randomized quicksort

insertion sort

Array $A[1] \dots A[n]$

for $i = 2 \dots n-1$ {

$T = A[i]$

$j = i-1$

 while $j \geq 0 \ \&\& \text{“compare” } T < A[j]$ {

“swap” { $A[j+1] = A[j]$

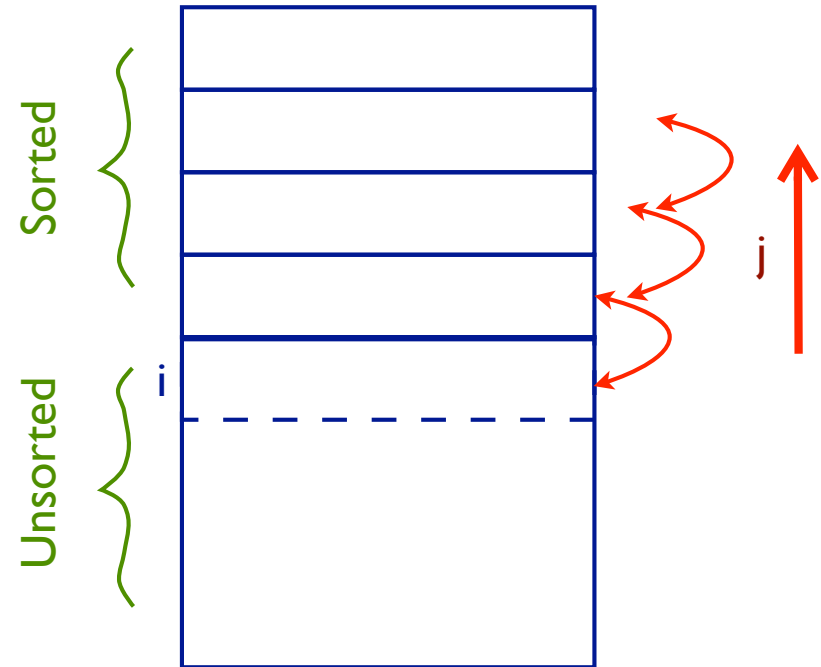
$A[j] = T$

$j = j-1$

}

$A[j+1] = T$

or



Run Time

Worst Case: $O(n^2)$

($\binom{n}{2}$ swaps; #compares = #swaps + $n - 1$)

“Average Case”

? What’s an “average” input?

One idea (and about the only one that is analytically tractable): **assume all $n!$ permutations of input are equally likely.**

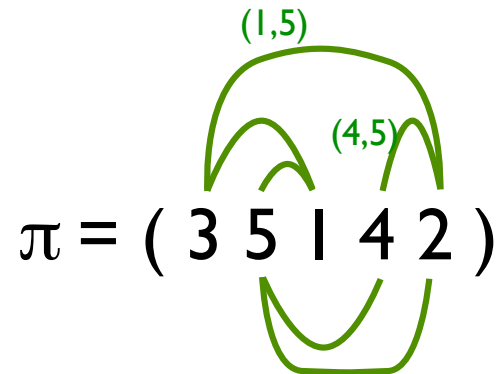
permutations & inversions

A *permutation* $\pi = (\pi_1, \pi_2, \dots, \pi_n)$ of $1, \dots, n$ is simply a list of the numbers between 1 and n , in some order.

(i,j) is *an inversion* in π if $i < j$ but $\pi_i > \pi_j$

G. Cramer, 1750

E.g.,



has six inversions: $(1,3)$, $(1,5)$, $(2,3)$, $(2,4)$, $(2,5)$, and $(4,5)$

Min possible: 0:

$$\pi = (1\ 2\ 3\ 4\ 5)$$

Max possible: n choose 2:

$$\pi = (5\ 4\ 3\ 2\ 1)$$

Obviously, the goal of sorting is to remove inversions

inversions & insertion sort

Swapping an *adjacent* pair of positions that are *out-of-order* decreases the number of inversions by *exactly 1*.

So..., number of swaps performed by insertion sort is exactly the number of inversions present in the input.

Counting them:

a. worst case: n choose 2

b. average case:

$$I_{i,j} = \begin{cases} 1 & \text{if } (i, j) \text{ is an inversion} \\ 0 & \text{if not} \end{cases}$$

$$I = \sum_{i < j} I_{i,j}$$

$$E[I] = E \left[\sum_{i < j} I_{i,j} \right] = \sum_{i < j} E [I_{i,j}]$$

“The method of indicators”

counting inversions

There is a 1-1 correspondence between permutations having inversion (i,j) versus *not*:

$$\begin{array}{c} \pi \quad (\dots \overset{i}{a} \dots \overset{j}{b} \dots) \\ \pi' \quad (\dots \underset{j}{b} \dots \underset{i}{a} \dots) \end{array}$$

So:

$$E[I_{i,j}] = P(I_{i,j} = 1) = 1/2$$

when π is chosen uniformly at random

$$E[I] = \sum_{i < j} E[I_{i,j}] = \sum_{i < j} \frac{1}{2} = \binom{n}{2} \cdot \frac{1}{2}$$

Thus, the expected number of swaps in insertion sort is $\binom{n}{2}/2$ versus $\binom{n}{2}$ in worst-case. I.e.,

The average run time of insertion sort (assuming random input) is about half the worst case time.

average-case analysis of quicksort

Quicksort also does swaps, but *nonadjacent* ones.

Recall method:

Array $A[1..n]$

1. “pivot” = $A[1]$

2. “Partition” ($O(n)$ compares/swaps) so that:

$\{A[1], \dots, A[i-1]\} < \{A[i] == \text{pivot}\} < \{A[i+1], \dots, A[n]\}$

3. recursively sort $\{A[1], \dots, A[i-1]\}$ & $\{A[i+1], \dots, A[n]\}$

Worst case: already sorted (among others) –

$$\begin{aligned} T(n) &= n + T(n-1) \Rightarrow \\ &= n + (n-1) + (n-2) + \dots + 1 = n(n+1)/2 \end{aligned}$$

Best case: pivot is always median

$$\begin{aligned} T(n) &= 2 T(n/2) + n \\ &\Rightarrow \sim n \log_2 n \end{aligned}$$

Average case: ?

Below. Will turn out to be ~40% slower than best
Why?

Random pivots are “near the middle on average”

Assume input is a random permutation of $1, \dots, n$, i.e., that all $n!$ permutations are equally likely

Then 1st pivot $A[l]$ is uniformly random in $1, \dots, n$

Important subtlety:

pivots at all recursive levels will be random, too,
(unless you do something funky in the partition phase)

number of comparisons

Let C_N be the average number of comparisons made by quicksort when called on an array of size N . Then:

$$C_0 = C_1 = 0 \quad (\text{a list of length } \leq 1 \text{ is already sorted})$$

In the general case, there are $N-1$ comparisons: the pivot vs every other element (a detail: plus 2 more for handling the “pointers cross” test to end the loop). The pivot ends up in some position $1 \leq k \leq N$, leaving two subproblems of size $k-1$ and $N-k$. By Law of Total Expectation:

$$C_N = N + 1 + \frac{1}{N} \sum_{1 \leq k \leq N} (C_{k-1} + C_{N-k}) \quad \text{for } N \geq 2,$$

$1/N$ because all values $1 \leq k \leq N$
for pivot are equally likely.

(Analysis from Sedgewick, *Algorithms in C*, 3rd ed., 1998, p311-312; Knuth TAOCP v3, 1st ed 1973, p120.)

$$C_N = N + 1 + \frac{1}{N} \sum_{1 \leq k \leq N} (C_{k-1} + C_{N-k}) \quad \text{for } N \geq 2,$$

Rearrange; every C_i is there twice

$$C_N = N + 1 + \frac{2}{N} \sum_{1 \leq k \leq N} C_{k-1}.$$

Multiply by N ;
subtract same
for $N-1$

$$NC_N - (N-1)C_{N-1} = N(N+1) - (N-1)N + 2C_{N-1}.$$

Rearrange

$$NC_N = (N+1)C_{N-1} + 2N.$$

$$NC_N = (N + 1)C_{N-1} + 2N.$$

$$\frac{C_N}{N + 1} = \frac{C_{N-1}}{N} + \frac{2}{N + 1}$$

$$= \frac{C_{N-2}}{N-1} + \frac{2}{N} + \frac{2}{N+1}$$

$$= \vdots$$

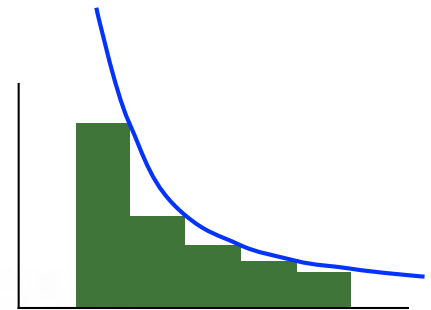
$$= \frac{C_2}{3} + \sum_{3 \leq k \leq N} \frac{2}{k+1}.$$

$$\frac{C_N}{N+1} \approx 2 \sum_{1 \leq k < N} \frac{1}{k} \approx 2 \int_1^N \frac{1}{x} dx = 2 \ln N,$$

$$2N \ln N \approx 1.39N \lg N$$

div by $N(N+1)$

substitute



So, *average* run time, averaging over *randomly ordered inputs*, = $\Theta(n \log n)$.

Every specific *worst case input is still worst case:*
n² every time

(Is real data random?)

Is it possible to improve the worst case?

another idea: randomize the algorithm

Algorithm as before, except pivot is a *randomly selected* element of $A[1] \dots A[n]$ (at top level; $A[i] \dots A[j]$ for subproblem $i..j$)

Analysis is the same, but conclusion is different:

On *any* fixed input, average run time is $n \log n$,
averaged over repeated (random) runs of the algorithm.

There are no longer any “bad inputs”, just “bad (random) choices.” Fortunately, such choices are improbable!

Average Case Analysis (of a deterministic alg w/ random input):

1. for algorithm A, choose a sample space S and probability distribution P from which inputs are drawn
2. for $x \in S$, let $T(x)$ be the time taken by A on input x
3. calculate, as a function of the “size,” n, of inputs,
$$\sum_{x \in S} T(x) \cdot P(x)$$
which is the expected or average run time of A

For sorting, distrib is usually “all n! permutations equiprobable”

Insertion sort: $E[\text{time}] \propto E[\text{inversions}] = \binom{n}{2} / 2 = \Theta(n^2)$,
about half the worst case

Quicksort: $E[\text{time}] = \Theta(n \log n)$ vs $\Theta(n^2)$ in worst case;
fun with recurrences, sums & integrals

Randomized Algorithms (with non-random, worst-case input):

1. for a randomized algorithm A , *input* x is fixed, just as usual, from some space I of possible inputs, but the algorithm may draw (and use) random samples $y = (y_1, y_2, \dots)$ from a given sample space S and probability distribution P . E.g., $y_i =$ “which pivot in subproblem i ”
2. for *any* $x \in I$ and any $y \in S$, let $T(x,y)$ be the time taken by A on input x when y is sampled from S
3. calculate, as a function of the “size,” n , of inputs,
$$\max_{x \in I} \sum_{y \in S} T(x,y) \cdot P(y)$$
which is the expected or average run time of A on a worst-case input

Randomized Quicksort: choosing pivots at random,
 $E[\text{time}] = \Theta(n \log n)$ for *any* input. (For every input, there are some rare random choice sequences causing n^2 time.)

Key distinction:

If average case analysis of a (deterministic) algorithm D says that average runtime \ll worst case, then worst case inputs must be rare. *But if you get one, your bad luck is permanent: D will be slow time after time after time on that input...*

If expected run time of a randomized algorithm R is \ll worst case, some inputs may be worse than others, but *there are no bad inputs*. If R runs slowly (near worst case) once, on a specific input, *your bad luck is transient; if you run it again you can expect it to run near the overall expectation.*

Worst-case analysis is much more common than *average-case* analysis because:

- It's often easier

- To get meaningful average case results, a reasonable probability model for “typical inputs” is critical, but may be unavailable, or difficult to analyze

- The results are often similar (e.g., insertion sort)

But in some important examples, average-case is sharply better (e.g., quicksort)

Randomized algorithms are very important in many areas; sometimes easier to argue that bad stuff is rare than to deterministically circumvent it (e.g., randomized qsort)

- Fascinating and deep open problem: is this intrinsic?