

4. Average Time and Probabilistic Programs

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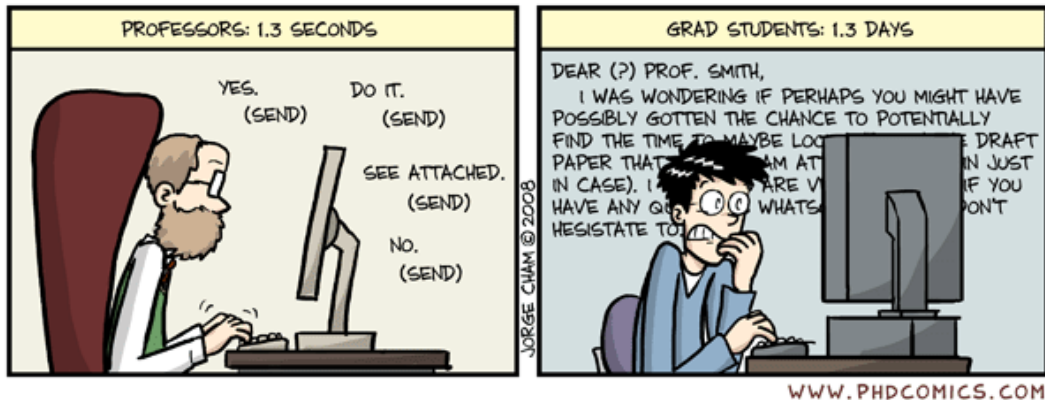
<https://fm-dcc.github.io/alg2425>



CISTER - Research Centre in
Real-Time & Embedded
Computing Systems

- Measuring precisely performance of algorithms
- Measuring asymptotically performance of algorithms
- Analysing recursive functions
- Measuring **precisely** the **average time** of algorithms
- Next: analysis of sequences of operations (**amortised analysis**)

AVERAGE TIME SPENT COMPOSING ONE E-MAIL



(from PhD comics: <https://phdcomics.com/comics/archive.php?comid=1047>)

```
int count = 0;
for (int i=0; i<n; i++)
    if (v[i] == 0) count++
```

RAM

- worst-case: $T(n) = 5 + 5n$
- best-case: $T(n) = 5 + 4n$

#array-accesses + #count-increments

- worst-case: $T(n) = 2n$
- best-case: $T(n) = n$
- average-case:
$$\overline{T}(n) = n + \sum_{0 \leq r < n} P(v[r] = 0)$$

Preliminaries: series

$$\sum_{i=1}^n i = 1 + 2 + \dots + n = \frac{n(n+1)}{2}$$

$$\sum_{i=a}^b i = a + (a+1) + \dots + b = \frac{(b-a+1)(a+b)}{2}$$

Intuition

[number of elements] \times [middle value]

$$\sum_{i=0}^n x^i = 1 + x + x^2 + \dots + x^n = \frac{x^{n+1} - 1}{x - 1}$$

Proof

Let $S = \sum_{i=0}^n x^i$. Then:

$$S \times x = x + x^2 + \dots + x^{n+1}$$

Hence we know $\left[(S \times x) - S = x^{n+1} - 1 \right]$.

Simplifying we get $\left[S = \frac{x^{n+1} - 1}{x - 1} \right]$.

$$\sum_{i=1}^n i \times x^{i-1} = x + (2 \times x^2) + \dots + (n \times x^n) = \frac{n \times x^{n+1} - (n+1) \times x^n + 1}{(x-1)^2}$$

Proof

Recall $\left[S = \sum_{i=1}^n x^i = \frac{x^{n+1}-1}{x-1} \right]$. Derive both:

$$\begin{aligned} S' &= (1 + x + x^2 + \dots + x^n)' = 0 + 1 + 2x + \dots + n \times x^{n-1} = \sum_{i=1}^n i \times x^{i-1} \\ &= \left(\frac{x^{n+1}-1}{x-1} \right)' = \frac{n \times x^{n+1} - (n+1) \times x^n + 1}{(x-1)^2} \end{aligned}$$

Calculating average cases

The average time to execute an algorithm is given as the **expected value** for its execution, assuming that each run r has a cost c_r and a probability p_r .

Expected cost

$$\overline{T}(N) = \sum_{r \in \text{Runs}} p_r \times c_r$$

```
int lsearch(int x, int N, int v[])
{
    // pre: sorted array v
    int i;
    i = 0;
    while ((i < N) && (v[i] < x))
        i++;
    if ((i == N) || (v[i] != x))
        return (-1);
    else return i;
}
```

- Count array accesses
- Best case: $T(N) = 2$
- Worst case: $T(N) = N + 1$
- Average case: $\overline{T}(N) = \dots$

```
int lsearch(int x, int N, int v[])
{
    // pre: sorted array v
    int i;
    i = 0;
    while ((i < N) && (v[i] < x))
        i++;
    if ((i == N) || (v[i] != x))
        return (-1);
    else return i;
}
```

- Count array accesses
- Best case: $T(N) = 2$
- Worst case: $T(N) = N + 1$
- Average case: $\overline{T}(N) = \dots$
 - assuming array with uniformly distributed values and a random x
 - same probability to do $0, 1, \dots, N - 1$ cycle iterations
 - Hence: N different runs, each
 - probability: $1/N$
 - cost: $\#cycles + 1$

```
int lsearch(int x, int N, int v[])
{
    // pre: sorted array v
    int i;
    i = 0;
    while ((i < N) && (v[i] < x))
        i ++;
    if ((i == N) || (v[i] != x))
        return (-1);
    else return i;
}
```

$$\overline{T}(N) = \sum_{i=1}^N \frac{1}{N} \times (i + 1)$$

```
int lsearch(int x, int N, int v[])
{
    // pre: sorted array v
    int i;
    i = 0;
    while ((i < N) && (v[i] < x))
        i++;
    if ((i == N) || (v[i] != x))
        return (-1);
    else return i;
}
```

$$\begin{aligned}\overline{T}(N) &= \sum_{i=1}^N \frac{1}{N} \times (i + 1) \\ &= \frac{1}{N} \times \sum_{i=1}^N (i + 1) \\ &= \frac{1}{N} \times \sum_{i=2}^{N+1} i \\ &= \frac{1}{N} \times \frac{N \times (N + 3)}{2} \\ &= \frac{N + 3}{2}\end{aligned}$$

```
int bsearch(int x, int N, int v[])
{
    int i,s,m;
    i=0; s=N-1;
    while (i<s){
        m= (i+s)/2;
        if (v[m] == x) i = s = m;
        else if (v[m] > x) s = m-1;
        else i = m+1;
    }
    if ((i>s) || (v[i] != x))
        return (-1);
    else return i;
}
```

Ex. 4.1: Calculate best/worst/average cases

- Count array accesses / nr. cycles
- Best case: $T(N) = ?$
- Worst case: $T(N) = ?$
- Average case: $\overline{T}(N) = ?$

- Example: $N=15$, worst case
 - 1st cycle: check $v[N/2]$ (7 remaining)
 - 2nd cycle: check $v[N/4]$ (or $v[3N/4]$ – 3 remaining)
 - 3rd cycle: check $v[N/8]$ (or $v[3N/8]$... – 1 remaining)
 - after: check $v[N/16]$ (or $v[3N/16]$...) if equal to x
- $N=15$, (3 cycles) \rightarrow 4 “cycles”
- In general: c cycles for $2^c - 1$ elements
- ... i.e., $N = 2^c - 1 \quad \equiv \quad c = \log_2(N + 1)$

- In an array of size N , there are $N+1$ cases (finding at a given position, or not finding).
- Assume $N+1$ cases have equal probability (!)
- Example: $N=15$
 - 1 cycle: find at $v[N/2]$ – prob. $\frac{1}{N+1}$
 - 2 cycles: find at $v[N/4]$ or $v[3N/4]$ – prob. $\frac{2}{N+1}$
 - 3 cycles: find at $v[N/8]$ or (...) – prob. $\frac{4}{N+1}$
 - after: find (or not) at $v[N/16]$ (...) – prob. $\frac{8}{N+1}$
- $N=15$, average cycles: $1 \times \frac{1}{N+1} + 2 \times \frac{2}{N+1} + 3 \times \frac{4}{N+1} + 4 \times \frac{8}{N+1}$
- In general: $1 \times \frac{1}{N+1} + \dots + \log_2(N+1) \times \frac{2^{\log_2(N+1)-1}}{N+1}$
- ... i.e., $\overline{T}(N) = \sum_{i=1}^{\log_2(N+1)} i \times \frac{2^{i-1}}{N+1} = \dots$

```
void twoComplement(char b[], int N)
{
    int i = N-1;
    while (i>0 && !b[i])
        i--;
    i--;
    while (i >=0) {
        b[i] = !b[i];
        i--;
    }
}
```

Ex. 4.2: Calculate best/worst/average cases

- Count nr. *bit updates*
- Best case: $T(N) = ?$
- Worst case: $T(N) = ?$
- Average case: $\overline{T}(N) = ?$

```
void twoComplement(char b[], int N)
{
    int i = N-1;
    while (i>0 && !b[i])
        i--;
    i--;
    while (i >=0) {
        b[i] = !b[i];
        i--;
    }
}
```

Ex. 4.3: Calculate best/worst/average cases

- Count nr. *bit updates*
- Best case: $T(N) = ?$
- Worst case: $T(N) = ?$
- Average case: $\overline{T}(N) = ?$

twoComplement(0001) = 1111 – 1 vs -1

twoComplement(0010) = 1110 – 2 vs -2

twoComplement(0011) = 1101 – 3 vs -3

twoComplement(01010000) = 10110000

```
int maxgrow(int v[], int N) {  
    int r = 1, i = 0, m;  
    while (i < N-1) {  
        m = grow(v+i, N-i);  
        if (m > r) r = m;  
        i++;  
    }  
    return r;  
}
```

```
int grow(int v[], int N) {  
    int i;  
    for (i=1; i < N; i++)  
        if (v[i] < v[i-1]) break;  
    return i;  
}
```

Ex. 4.4: How many comparison of array elements exist in the average case for `grow`? (assume $v[i] < v[i-1]$ has 50% chances of succeeding)

Ex. 4.5: How many comparison of array elements exist in the average case for `maxgrow`?

```
void iSort(int v[], int N){  
    int i, j;  
    for (i=1; i<N; i++)  
        for (j=i; j>0 && v[j-1]>v[j];  
            j--)  
            swap(v, j, j-1);  
}
```

Ex. 4.6: How many comparison of array elements exist in the average case?
(as before, assume $v[j-1] > v[j]$ has 50% chances of succeeding)

```
int partition(int N, int v[]){
    int i, j=0;
    for (i=0; i<N-1; i++)
        if (v[i]<v[N-1])
            swap(v,i,j++);
    swap(v,N-1,j);
    return j ;
}
```

```
void quickSort(int N, int v[]){
    int p;
    if (N>1) {
        p = partition(N, v);
        quickSort(v, p);
        quickSort(v+p+1, N-p-1);
    }
}
```

(See animation at <https://visualgo.net/en/sorting>)

Partition

- Comparisons: $T_{\text{partition}}(N) = N - 1$ in any case
- Swaps: $T_{\text{partition}}(N) = N$ in the worst case, 1 in the best case

Quicksort (comparisons)

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort (comparisons) in general

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort (comparisons) when $p = 0$

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(N - 1) & \text{if } N > 1 \end{cases}$$

Quicksort (comparisons) in general

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort (comparisons) when $p = 0$

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(N - 1) & \text{if } N > 1 \end{cases}$$

$$\begin{aligned} T(N) &= (N - 1) + (N - 2) + \dots + 2 + 1 \\ &= \sum_{i=1}^{N-1} i = \frac{N(N - 1)}{2} = \Theta(N^2) \end{aligned}$$

Quicksort (comparisons) in general

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort when $p = \frac{N-1}{2}$

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + 2T(\frac{N-1}{2}) & \text{if } N > 1 \end{cases}$$

Quicksort (comparisons) in general

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort when $p = \frac{N-1}{2}$

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + 2T(\frac{N-1}{2}) & \text{if } N > 1 \end{cases}$$

$$\begin{aligned} T(N) &= ???(\text{use recurrence trees}) \\ &= \Theta(N \times \log(N)) \end{aligned}$$

Quicksort (comparisons) in general

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort when p can be any with equal probability

$$\bar{T}(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + \sum_{p=0}^{N-1} \frac{1}{N} (\bar{T}(p) + \bar{T}(N - p - 1)) & \text{if } N > 1 \end{cases}$$

Quicksort (comparisons) in general

$$T(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + T(p) + T(N - 1 - p) & \text{if } N > 1, \text{ where } 0 \leq p < N \end{cases}$$

Quicksort when p can be any with equal probability

$$\bar{T}(N) = \begin{cases} 0 & \text{if } N = 1 \\ N - 1 + \sum_{p=0}^{N-1} \frac{1}{N} (\bar{T}(p) + \bar{T}(N - p - 1)) & \text{if } N > 1 \end{cases}$$

$$\begin{aligned} \sum_{p=0}^{N-1} \frac{1}{N} (\bar{T}(p) + \bar{T}(N - p - 1)) &= \frac{1}{N} \times \sum_{p=0}^{N-1} \bar{T}(p) + \frac{1}{N} \times \sum_{p=0}^{N-1} \bar{T}(N - p - 1) \\ &= \frac{1}{N} \times \sum_{p=0}^{N-1} \bar{T}(p) + \frac{1}{N} \times \sum_{p=0}^{N-1} \bar{T}(p) = \frac{2}{N} \times \sum_{p=0}^{N-1} \bar{T}(p) \end{aligned}$$

$$\overline{T}(N) = N - 1 + \sum_{p=0}^{N-1} \frac{1}{N} (\overline{T}(p) + \overline{T}(N - p - 1)) = N - 1 + \frac{2}{N} \times \sum_{p=0}^{N-1} \overline{T}(p)$$

Multiplying by N

$$N \times \overline{T}(N) = N \times (N - 1) + 2 \times \sum_{p=0}^{N-1} \overline{T}(p)$$

Applying for $N - 1$

$$(N - 1) \times \overline{T}(N - 1) = (N - 1) \times (N - 2) + 2 \times \sum_{p=0}^{N-2} \overline{T}(p)$$

Subtracting each side

$$\begin{aligned} N \times \overline{T}(N) - (N - 1) \times \overline{T}(N - 1) = \\ N \times (N - 1) + 2 \times \sum_{p=0}^{N-1} \overline{T}(p) - (N - 1) \times (N - 2) - 2 \times \sum_{p=0}^{N-2} \overline{T}(p) \end{aligned}$$

Subtracting each side

$$\begin{aligned} N \times \overline{T}(N) - (N-1) \times \overline{T}(N-1) &= \\ N \times (N-1) + 2 \times \sum_{p=0}^{N-1} \overline{T}(p) - (N-1) \times (N-2) - 2 \times \sum_{p=0}^{N-2} \overline{T}(p) \end{aligned}$$

Simplifying

$$\begin{aligned} \overline{T}(N) &= \left(\frac{2N-1}{N} \right) + \left(\frac{N+1}{N} \right) \times \overline{T}(N-1) \\ &= \dots \\ &= \Theta(N \times \log(N)) \end{aligned}$$

Subtracting each side

$$\begin{aligned} N \times \overline{T}(N) - (N-1) \times \overline{T}(N-1) &= \\ N \times (N-1) + 2 \times \sum_{p=0}^{N-1} \overline{T}(p) - (N-1) \times (N-2) - 2 \times \sum_{p=0}^{N-2} \overline{T}(p) \end{aligned}$$

Simplifying

$$\begin{aligned} \overline{T}(N) &= \left(\frac{2N-1}{N} \right) + \left(\frac{N+1}{N} \right) \times \overline{T}(N-1) \\ &= \dots \\ &= \Theta(N \times \log(N)) \end{aligned}$$

Randomised Quicksort – the version usually used – uses a **random pivot** when partitioning.

Randomised Algorithms

slides by Pedro Ribeiro, slides 4
pages 9-13

Randomized Algorithms

Randomized algorithms

We call an algorithm **randomized** if its behavior is determined not only by its input but also by values produced by a **random-number generator**

- Most programming environments offer a (deterministic) **pseudorandom-number generator**: it returns numbers that *"look"* statistically random
- We typically refer to the analysis of randomized algorithms by talking about the **expected cost** (ex: the **expected running time**)
- We can use **probabilistic analysis** to analyse randomized algorithms

Basics of Probabilistic Analysis

- Consider rolling **two dice** and observing the results.
- We call this an **experiment**.
- It has **36 possible outcomes**:
1-1, 1-2, 1-3, 1-4, 1-5, 1-6, 2-1, 2-2, 2-3, ..., 6-4, 6-5, 6-6
- Each of these outcomes has probability **$1/36$** (assuming fair dice)
- What is the probability of the sum of dice being 7?
Add the probabilities of all the outcomes satisfying this condition:
1-6, 2-5, 3-4, 4-3, 5-2, 6-1 (probability is **$1/6$**)



Basics of Probabilistic Analysis

In the language of probability theory, this setting is characterized by a **sample space** S and a **probability measure** p .

- **Sample Space** is constituted by all possible outcomes, which are called **elementary events**
- In a **discrete probability distribution** (d.p.d.), the probability measure is a function $p(e)$ (or $Pr(e)$) over elementary events e such that:
 - ▶ $p(e) \geq 0$ for all $e \in S$
 - ▶ $\sum_{e \in S} p(e) = 1$
- An **event** is a subset of the sample space.
- For a d.p.d. the probability of an event is just the **sum** of the probabilities of its elementary events.

Basics of Probabilistic Analysis

- A **random variable** is a function from elementary events to integers or reals:

Ex: let X_1 be a random variable representing result of first die and X_2 representing the second die.

$X = X_1 + X_2$ would represent the sum of the two

We could now ask: what is the probability that $X = 7$?

- One property of a random variable we care is **expectation**:

Expectation

For a discrete random variable X over sample space S , the expected value of X is:

$$\mathbf{E}[X] = \sum_{e \in S} \text{Pr}(e)X(e)$$

Basics of Probabilistic Analysis

- In **words**: the expectation of a random variable X is just its average value over S , where each elementary event e is weighted according to its probability.

Ex: If we roll a single die, the expected value is 3.5
(all six elementary events have equal probability).

- One possible rewrite of the previous equation, grouping elementary events:

Expectation (possible rewrite)

$$E[X] = \sum_a Pr(X = a)a$$

- QuickSort always returns a **correct result** (a sorted array) but its **runtime is a random variable** (with $\mathcal{O}(n \log n)$ in expectation)
- Some randomized algorithms are **not guaranteed to be correct**, but their **runtime is fixed**.

Las Vegas Algorithms

Randomized algorithms that always output the correct answer, and whose runtimes are random variables.

Monte Carlo Algorithms

Randomized algorithms that always terminate in a given time bound, but are correct with at least some (high) probability.