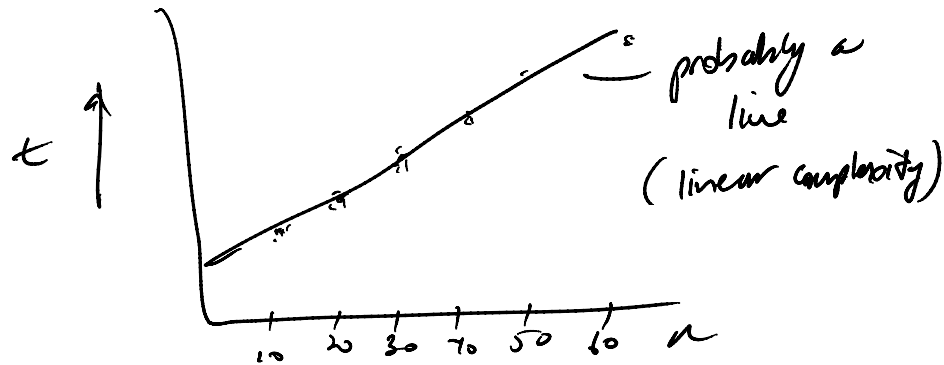


Algorithm Analysis (Chp. 2)

- How do we compare the running time of algorithms?
- The empirical approach:
 - ↳ experiments, observation
 - use your Timer class, place start(), stop() around code fragments (e.g. sort)
 - collect running time of a piece of code
 - will running it once suffice? No
 - why not?
 - diff. platform (CPU, memory, OS)
 - # of tasks running on CPU (warning for multitasking OS)
 - need statistics broadly

```
int sum(int n)
{
    int partialSum;
    Timer t;
    t.start();
    partialSum = 0;
    for (int i = 1; i <= n; i++) partialSum += i * i * i;
    t.end();
    cout << "took " << t.elapsed_ms() << " ms" << endl;
    return partialSum;
}
```

Run it several times, changing n at random; plot



- empirical approach is nice, but we'd like to be able to predict running time
- can do this by counting # execution steps of alg.

operation count

```

int sum (int n)
{
    int ps;
    for (int i=1; i <= n; i++)
        ps += i * i * i;
    return ps;
}

```

Annotations for operation count:

- 0 for the opening brace of the function.
- $0N+2$ for the for loop header (initialization and condition).
- $4N$ for the body of the for loop (assignment and multiplication).
- 1 for the return statement.
- $0+1 + (2N+2) + (4N+1) = 6N+4$ for the total operation count.

Other annotations:

- $N+1$ for the number of iterations of the for loop.
- N for the number of iterations of the body of the for loop.
- $\# operations,$ and $\# statements$ for the total number of operations and statements.
- $- declarations = 0$ for the number of declarations.

- Basic rules:

1. for loops: # statements inside * iterations

2. nested for loops:

- analyze inside-out

- product of all loops

$$\begin{array}{l} \text{for } (i=0; i < n; i++) \\ n \left[\begin{array}{l} \text{for } (j=0; j < n; j++) \\ n \left[\begin{array}{l} \text{for } (k=0; k < n; k++) \\ \text{statements} \end{array} \right] \end{array} \right] \end{array}$$

$$n \times n = n^2$$

3. Consecutive statements: just add up

4. conditionals: use larger of the branches

5. recursion: the tricky one

- will come back to that one

- given ^(or actual #) estimate of # statements, come up with asymptotic function to describe order (magnitude) of statements.

e.g. $6N+4 \approx O(N)$

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 $T(N)$ \nearrow \nwarrow by definition: "order N "

same class of
function in asymptotic sense \sim only differs
in some
constant
amount.

- more formally

$$T(n) = O(f(n)) \text{ if } \exists c, n_0 \text{ s.t. } T(n) \leq c f(n) \text{ where } n \geq n_0$$

let's say $T(N) = N+1$

$$N+1 \leq cN \text{ where } N \geq n_0 \text{ if we let}$$

$$n_0 \approx 100, \quad c \approx 2$$

✓ $100+1 \leq 200$

$$(N+1) \in O(N)$$

basically, we can drop the constants

- in general, we can drop the constants, & lower order terms

$$\text{e.g. } T(N) = O(\cancel{4}N^2 + N) = O(N^2 + \cancel{N}) = O(N^2)$$

- big-oh $O(f(N))$ specifies upper bound -
practically speaking, worst-case running time
of alg

- other important analytical definitions:

$$\Omega(g(n))$$

$$T(n) = \Omega(g(n)) \text{ if } \exists c, n_0 \mid T(n) \geq cg(n)$$

means that $g(n)$ is the alg's lower bound —
alg must run at least as fast as this
(best case analysis)

$$T(n) = \Theta(h(n)) \text{ iff } T(n) = O(h(n)) = \Omega(h(n))$$

this is used to denote average running time

finally,

little-oh

$$T(n) = o(p(n)) \text{ if } \forall c \exists n_0 \mid T(n) < c p(n) \text{ when } n > n_0$$

big-oh allows \leq
equality

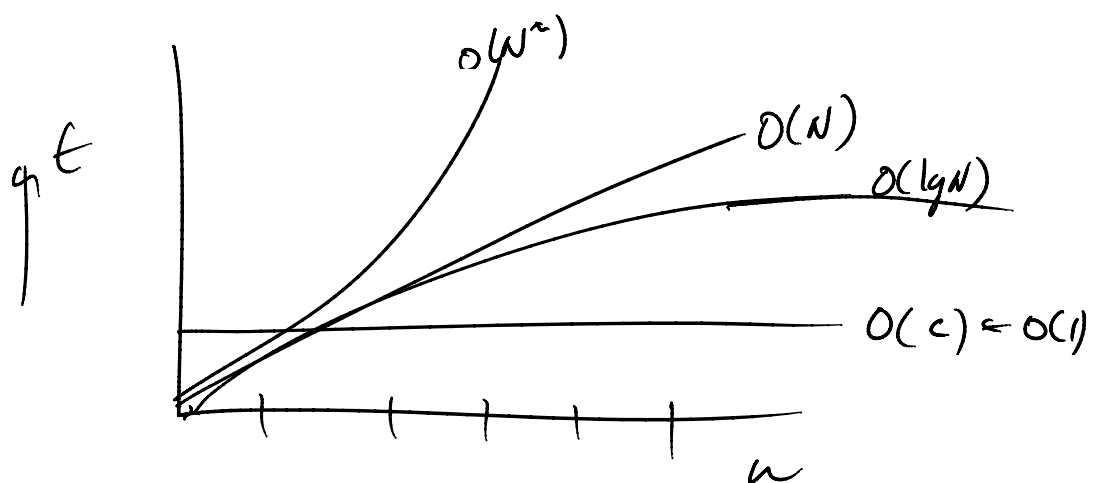
- what's the big idea? want to compare
relative running times (bounds) of algs.

(empirical approach: sort of an absolute metric —
here we want relative & predictive)

- relative orders:

$$\begin{array}{ccccccccc} O(1) & < & O(\lg N) & < & O(\lg^2 N) & < & O(N) & < & O(N \lg N) \\ \text{constant} & & \text{logarithmic} & & \text{iterated logarithmic} & & \text{linear} & & \text{log linear} \end{array}$$
$$\begin{array}{ccccccc} & & & < & O(N^2) & < & O(N^3) & < & O(2^N) \\ & & & & \text{quadratic} & & \text{cubic} & & \text{exponential} \end{array}$$

$\Theta(N \lg N)$
↓
this describes growth rates



5. Recursion: the tricky one

— involves solving recurrence relations
RECURRENCE

(or proving, e.g. by induction)

e.g. long fib(int n)

2 if ($n \leq 1$) return 1

3 else return $\text{fib}(n-1) + \text{fib}(n-2)$

$T(0) = T(1) = 1$

$T(n) = T(n-1) + T(n-2)$

How to solve?

- for $n > 4$, $T(n) \geq \left(\frac{3}{2}\right)^n$ Exponential

- prove by induction

$$T(n) = T(n-1) + T(n-2) \geq \left(\frac{3}{2}\right)^n$$

assume it holds for $n > 4$

show $T(n+1) \geq \left(\frac{3}{2}\right)^{n+1}$ from

$$T(n+1) = T(n+1-1) + T(n+1-2)$$

$$= T(n) + T(n-1)$$

$$\left(\frac{3}{2}\right)^n + \left(\frac{3}{2}\right)^{n-1}$$

want to get it in terms of $\left(\frac{3}{2}\right)^{n+1}$ so we get

$$\left(\frac{3}{2}\right)^n + \left(\frac{3}{2}\right)^{n-1}$$

$$= \left(\frac{3}{2}\right)^{-1} \left(\frac{3}{2}\right)^{n+1} + \left(\frac{3}{2}\right)^{-1} \left(\frac{3}{2}\right)^{-1} \left(\frac{3}{2}\right)^{n+1}$$

$$= \left(\frac{2}{3}\right) \left(\frac{3}{2}\right)^{n+1} + \left(\frac{2}{3}\right)^2 \left(\frac{3}{2}\right)^{n+1}$$

$$= \left(\frac{2}{3} + \frac{4}{9}\right) \left(\frac{3}{2}\right)^{n+1} = \left(\frac{10}{9}\right) \left(\frac{3}{2}\right)^{n+1} \geq \left(\frac{3}{2}\right)^{n+1}$$

QED