

What Are the Questions?

Principal concern throughout engineering:
"The engineer is someone who can do for a dime what any fool can do for a dollar."
Main
Principal cost (for programs, time to run, space requirements).
Principal costs: How much engineering time? When delivered?
Failure: How robust? How safe?
How fast enough? Depends on:
- *purpose*;
- *input data*.
- *space* (memory, disk space)?
- *depends* on what input data.
- *scale*, as input gets big?

23:18 2017

CS61B: Lecture #16 2

Cost Measures (Time)

Principal execution time
- *do this at home*:
- *example*: java FindPrimes 1000
- *notes*: easy to measure, meaning is obvious.
- *note*: where time is critical (real-time systems, e.g.).
- *notes*: applies only to specific data set, compiler, machine.
- *notes*: times certain statements are executed:
- *notes*: more general (not sensitive to speed of machine).
- *notes*: doesn't tell you actual time, still applies only to specific data sets.
- *notes*: execution times:
- *formulas* for execution times as functions of input size.
- *notes*: applies to all inputs, makes scaling clear.
- *note*: practical formula must be approximate, may tell you about actual time.

23:18 2017

CS61B: Lecture #16 4

Handy Tool: Order Notation

Principal
- *try* to produce *specific* functions that specify size, but *avoid* *classes* of *similar* functions.
- *note*: saying like "*f* is bounded by *g* if it is in *g*'s family."
- *note*: for a function $g(x)$, the functions $2g(x)$, $1000g(x)$, or for any $K > 0$ all have the same "shape". So put all of them into *g*'s family.
- *note*: find $h(x)$ such that $h(x) = K \cdot g(x)$ for $x > M$ (for some M) has *g*'s shape "except for small values." So put all of them into *g*'s family.
- *note*: upper limits, throw in all functions that are everywhere bounded by *g*'s family. Call this family $O(g)$ or $O(g(n))$.
- *note*: lower limits, throw in all functions that are everywhere bounded by *g*'s family. Call this family $\Omega(g)$.
- *note*: the $\Theta(g) = O(g) \cap \Omega(g)$ —the set of functions bracketed by *g*'s family.

23:18 2017

CS61B: Lecture #16 6

CS61B Lecture #16: Complexity

Principal
- *contest* 14 October. Details to follow.

23:18 2017

CS61B: Lecture #16 1

Enlightening Example

Principal
- *note*: a text corpus (say 10^7 bytes or so), and find and print frequently used words, together with counts of how often they appear.
- *note*: (math): Heavy-Duty data structures
- *note*: *implementation*, randomized placement, pointers general pages long.
- *note*: Doug McIlroy): UNIX shell script:
- *code*:

```
'[:alpha:]' | tr -d '\n' < FILE | \
\
tr -k 1,1 | \
```


- *note*: faster,
- *note*: took 5 minutes to write and processes 30MB in < 8 sec.
- *note*:
- *note*: *notes*, anything will do: Keep It Simple.

23:18 2017

CS61B: Lecture #16 3

Asymptotic Cost

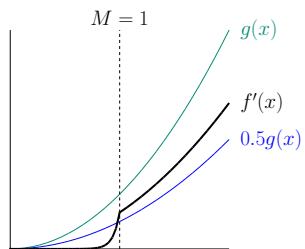
Principal
- *note*: execution time lets us see *shape* of the cost function.
- *note*: approximating anyway, pointless to be precise about constants.
- *note*: on small inputs:
- *note*: says pre-calculate some results.
- *note*: for small inputs not usually important.
- *note*: constant factors (as in "off by factor of 2"):
- *note*: changing machines causes constant-factor change.
- *note*: don't get fact away from (i.e., ignore) these things?

23:18 2017

CS61B: Lecture #16 5

Big Omega

Lower bounding from below:



$f(x) \geq \frac{1}{2}g(x)$ as long as $x > 1$,

$f(x)$'s lower-bound family, written

$$f(x) \in \Omega(g(x)),$$

though $f(x) < g(x)$ everywhere.

23:18 2017

CS61B: Lecture #16 8

How We Use Order Notation

In mathematics, you'll see $O(\dots)$, etc., used generally to describe bounds on functions.

$$\pi(N) = \Theta\left(\frac{N}{\ln N}\right)$$

and we prefer to write

$$\pi(N) \in \Theta\left(\frac{N}{\ln N}\right)$$

where $\pi(N)$ is the number of primes less than or equal to N .

Some things like

$$f(x) = x^3 + x^2 + O(x),$$

where $f(x) = x^3 + x^2 + g(x)$ where $g(x) \in O(x)$.

Usually, the functions we will be bounding will be *cost functions* that measure the amount of execution time or the space required by a program or algorithm.

23:18 2017

CS61B: Lecture #16 10

Some Intuition on Meaning of Growth

How many problems can you solve in a given time?

The following table, left column shows time in microseconds to solve a problem as a function of problem size N .

For a given *size of problem* that can be solved in a second, (31 days), and century, for various relationships between time required and problem size.

Problem size

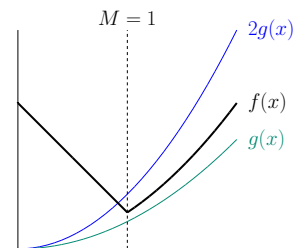
Problem size for N	1 second	Max N Possible in 1 hour	1 month	1 century
	10^{300000}	$10^{1000000000}$	$10^{8 \cdot 10^{11}}$	$10^{9 \cdot 10^{14}}$
	10^6	$3.6 \cdot 10^9$	$2.7 \cdot 10^{12}$	$3.2 \cdot 10^{15}$
	63000	$1.3 \cdot 10^8$	$7.4 \cdot 10^{10}$	$6.9 \cdot 10^{13}$
	1000	60000	$1.6 \cdot 10^6$	$5.6 \cdot 10^7$
	100	1500	14000	150000
	20	32	41	51

23:18 2017

CS61B: Lecture #16 12

Big Oh

Upper bounding from above.



$f(x) \leq 2g(x)$ as long as $x > 1$,

$f(x)$'s upper-bound family, written

$$f(x) \in O(g(x)),$$

though (in this case) $f(x) > g(x)$ everywhere.

23:18 2017

CS61B: Lecture #16 7

Big Theta

From the previous slides, we not only have $f(x) \in O(g(x))$ and $f(x) \in \Omega(g(x))$,...

we also have $f(x) \in \Omega(g(x))$ and $f(x) \in O(g(x))$.

We can summarize this all by saying $f(x) \in \Theta(g(x))$ and $f(x) \in \Theta(g(x))$.

23:18 2017

CS61B: Lecture #16 9

Why It Matters

Scientists often talk as if constant factors didn't matter because of the difference of $\Theta(N)$ vs. $\Theta(N^2)$.

But constants do matter, but at some point, constants always get

\sqrt{n}	n	$n \lg n$	n^2	n^3	2^n
1.4	2	2	4	8	4
2	4	8	16	64	16
2.8	8	24	64	512	256
4	16	64	256	4,096	65,536
5.7	32	160	1024	32,768	4.2×10^9
8	64	384	4,096	262,144	1.8×10^{19}
11	128	896	16,384	2.1×10^9	3.4×10^{38}
:	:	:	:	:	:
32	1,024	10,240	1.0×10^6	1.1×10^9	1.8×10^{308}
:	:	:	:	:	:
1024	1.0×10^6	2.1×10^7	1.1×10^{12}	1.2×10^{18}	$6.7 \times 10^{315,652}$

23:18 2017

CS61B: Lecture #16 11

Be Careful

Be careful that the worst-case time is $O(N^2)$, since $N \in O(N^2)$ bounds are loose.

Best-case time is $\Omega(N)$, since $N \in \Omega(N)$, but that does not mean the loop always takes time N , or even $K \cdot N$ for some K .

We are just saying something about the function that maps the largest possible time required to process an array of size N .

As much as possible about our worst-case time, we should try to find a lower bound: in this case, we can: $\Theta(N)$.

That still tells us nothing about best-case time, which we find when we find X at the beginning of the loop. Best-case time is $\Theta(1)$.

Using the Notation

Order notation for any kind of real-valued function.

Use them to describe cost functions. Example:

```
int indexOf(List L, Object X) {
    // Position of X in list L, or -1 if not found. */
}
```

```
int c = 0; L != null; L = L.next, c += 1)
while (X.equals(L.head)) return c;
return -1;
```

Representative operation: number of `.equals` tests.

Length of L , then loop does at most N tests: worst-case tests.

Number of instructions executed is roughly proportional to worst case, so can also say worst-case time is $O(N)$, if units used to measure.

Special provision (in defn. of $O(\cdot)$) to handle empty list.

Division and Recurrences: Fast Growth

Cost of recursion. In the worst case, both recursive calls

```
if X is a substring of S */
int occurs(String S, String X) {
    if (S.equals(X)) return true;
    if (S.length() < X.length()) return false;
}
```

```
{S.substring(1), X} ||
{S.substring(0, S.length()-1), X};
```

Cost to be the worst-case cost of `occurs(S,X)` for S of fixed size N_0 , measured in # of calls to `occurs`. Then

$$C(N) = \begin{cases} 1, & \text{if } N \leq N_0, \\ 2C(N-1) + 1 & \text{if } N > N_0 \end{cases}$$

Grows exponentially:

$$C(N-1) + 1 = 2(2C(N-2) + 1) + 1 = \dots = 2(\dots 2 \cdot 1 + 1) + \dots + 1$$

$$N_0 + 2^{N-N_0-1} + 2^{N-N_0-2} + \dots + 1 = 2^{N-N_0+1} - 1 \in \Theta(2^N)$$

Effect of Nested Loops

Loops often lead to polynomial bounds:

```
int i = 0; i < A.length; i += 1)
while (int j = 0; j < A.length; j += 1)
    if (A[i] != A[j]) return true;
return false;
```

Complexity is $O(N^2)$, where $N = A.length$. Worst-case time is

Efficient though:

```
int i = 0; i < A.length; i += 1)
while (int j = i+1; j < A.length; j += 1)
    if (A[i] == A[j]) return true;
return false;
```

Worst-case time is proportional to

$$-1 + N - 2 + \dots + 1 = N(N-1)/2 \in \Theta(N^2)$$

Asymptotic time unchanged by the constant factor).

Another Typical Pattern: Merge Sort

```
mergeSort(L) {
    if (L.size() < 2) return L;
    List L1, L2;
    split(L, L1, L2); // L1 and L2 of about equal size;
    mergeSort(L1); // Merge ("combine into a single ordered list")
    mergeSort(L2); // takes time proportional to size of its result.
    return merge(L1, L2);
}
```

Cost at size of L is $N = 2^k$, worst-case cost function, $C(N)$, merge time (\propto # items merged):

$$C(N) = \begin{cases} 1, & \text{if } N < 2; \\ 2C(N/2) + N, & \text{if } N \geq 2. \end{cases}$$

$$= 2(2C(N/4) + N/2) + N$$

$$= 4C(N/4) + N + N$$

$$= 8C(N/8) + N + N + N$$

$$= N \cdot 1 + \underbrace{N + N + \dots + N}_{k=\lg N}$$

$$= N + N \lg N \in \Theta(N \lg N)$$

Complexity $\Theta(N \lg N)$ for arbitrary N (not just 2^k).

Binary Search: Slow Growth

```
boolean isIn(S[L..U], Object X) {
    // X is an element of S[L..U]. Assumes
    // sorted order, 0 <= L <= U-1 < S.length. */
    int lo = L, hi = U-1;
    while (lo <= hi) {
        int m = (lo+hi)/2;
        if (X.equals(S[m])) return true;
        else if (X.compareTo(S[m]) < 0) hi = m-1;
        else lo = m+1;
    }
    return false;
}
```

Worst-case time, $C(D)$, (as measured by # of string comparisons on size $D = U - L + 1$).

Remove $S[M]$ from consideration each time and look at half the size $D = 2^k - 1$ for simplicity, so:

$$C(D) = \begin{cases} 0, & \text{if } D \leq 0, \\ 1 + C((D-1)/2), & \text{if } D > 0. \end{cases}$$

$$= 1 + 1 + \dots + 1 + 0$$

$$= k = \lceil \lg D \rceil \in \Theta(\lg D)$$