CS61B Lecture #16

Announcements:

- CSUA help session on Subversion today 4-6PM in the Wozniak lounge (north side of Soda on 4th floor).
- Please use `bug-submit` for code problems.
- Watch the newsgroup and class web site for updates, hints, useful new utilities, etc.

Readings for Today: *Data Structures (Into Java),* Chapter 1;

Readings for next Topics: *Data Structures,* Chapter 2–4, *Head First Java,* Chapter 16.

What Are the Questions?

- Cost is a principal concern throughout engineering:

  "An engineer is someone who can do for a dime what any fool can do for a dollar."

- Cost can mean
  - Operational cost (for programs, time to run, space requirements).
  - Development costs: How much engineering time? When delivered?
  - Costs of failure: How robust? How safe?
- Is this program fast enough? Depends on:
  - *For what purpose;*
  - *What input data.*
- How much space (memory, disk space)?
  - Again depends on what input data.
- How will it scale, as input gets big?

Enlightening Example

Problem: Scan a text corpus (say 10^7 bytes or so), and find and print the 20 most frequently used words, together with counts of how often they occur.

- Solution 1 (Knuth): Heavy-Duty data structures
  - Hash Trie implementation, randomized placement, pointers galore, several pages long.
- Solution 2 (Doug McIlroy): UNIX shell script:

```
tr -c -s '[:alpha:]' '[\n*]' < FILE | \
sort | \
uniq -c | \
sort -n -r -k 1,1 | \
sed 20q
```

- Which is better?
  - #1 is much faster,
  - but #2 took 5 minutes to write and processes 20MB in 1 minute.
  - I pick #2.
- In most cases, anything will do: Keep It Simple.

Cost Measures (Time)

- Wall-clock or execution time
  - You can do this at home:

    ```
    time java FindPrimes 1000
    ```
  - Advantages: easy to measure, meaning is obvious.
  - Appropriate where time is critical (real-time systems, *e.g.*).
  - Disadvantages: applies only to specific data set, compiler, machine, etc.
- Number of times certain statements are executed:
  - Advantages: more general (not sensitive to speed of machine).
  - Disadvantages: doesn't tell you actual time, still applies only to specific data sets.
- Symbolic execution times:
  - That is, *formulas* for execution times or statement counts in terms of input size.
  - Advantages: applies to all inputs, makes scaling clear.
  - Disadvantage: practical formula must be approximate, may tell very little about actual time.

Asymptotic Cost

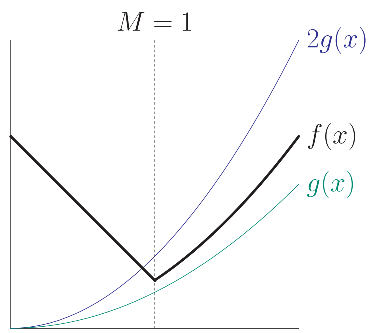
- Symbolic execution time lets us see *shape* of the cost function.
- Since we are approximating anyway, pointless to be precise about certain things:
  - Behavior on small inputs:
    - Can always pre-calculate results some results.
    - Times for small inputs not usually important.
  - Constant factors (as in "off by factor of 2"):
    - Just changing machines causes constant-factor change.
- How to abstract away from (i.e., ignore) these things?

Handy Tool: Order Notation

- Idea: Don't try to produce *specific* functions that specify size, but rather *families* of *similar* functions.
- Say something like "f is bounded by g if it is in g's family."
- For any function $g(x)$, the functions $2g(x)$, $1000g(x)$, or for any $K > 0$, $K \cdot g(x)$, all have the same "shape". So put all of them into g's family.
- Any function $h(x)$ such that $h(x) = K \cdot g(x)$ for $x > M$ (for some constant M) has g's shape "except for small values." So put all of these in g's family.
- If we want upper limits, throw in all functions that are everywhere $\leq$ some other member of g's family. Call this family $O(g)$ or $O(g(n))$.
- Or, if we want lower limits, throw in all functions that are everywhere $\geq$ some other member of g's family. Call this family $\Omega(g)$.
- Finally, define $\Theta(g) = O(g) \cap \Omega(g)$—the set of functions *bracketed by* members of g's family.

Big Oh

- Goal: Specify bounding from above.



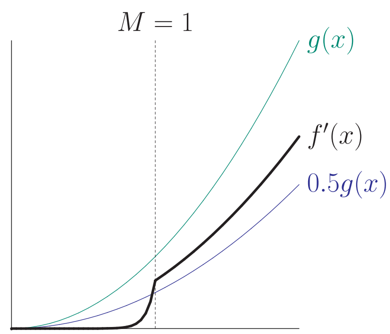
- Here, $f(x) \leq 2g(x)$ as long as $x > 1$,
- So $f(x)$ is in g's upper-bound family, written

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

- ... even though $f(x) > g(x)$ everywhere.

Big Omega

- Goal: Specify bounding from below:



- Here, $f'(x) \geq \frac{1}{2}g(x)$ as long as $x > 1$,
- So $f'(x)$ is in g's lower-bound family, written

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

- ... even though $f(x) < g(x)$ everywhere.
- In fact, we also have $f'(x) \in O(g(x))$ and $f(x) \in \Omega(g(x))$ and so we can also write

$$f(x), f'(x) \in \Theta(g(x)).$$

Using the Notation

- Can use this order notation for any kind of real-valued function.
- We will use them to describe cost functions. Example:

```
/** Find position of X in list L.  Return -1 if not found */
int find (List L, Object X) {
   int c;
   for (c = 0; L != null; L = L.next, c += 1)
      if (X.equals (L.head)) return c;
   return -1;
}
```

- Choose representative operation: number of `.equals` tests.
- If N is length of L, then loop does *at most* N tests: *worst-case time* is N tests.
- In fact, total # of instructions executed is roughly proportional to N in the worst case, so can also say worst-case time is $O(N)$, regardless of units used to measure.
- Use $N > M$ provision (in defn. of $O(\cdot)$) to handle empty list.

Why It Matters

- Computer scientists often talk as if constant factors didn't matter at all, only the difference of $\Theta(N)$ vs. $\Theta(N^2)$.
- In reality they do, but we still have a point: at some point, constants get swamped.

n	$16\lg n$	$\sqrt{n}$	n	$n\lg n$	n^2	n^3	2^n
2	16	1.4	2	2	4	8	4
4	32	2	4	8	16	64	16
8	48	2.8	8	24	64	512	256
16	64	4	16	64	256	$4,096$	$65,636$
32	80	5.7	32	160	1024	$32,768$	4.2×10^9
64	96	8	64	384	$4,096$	$262,144$	1.8×10^{19}
128	112	11	128	896	$16,384$	2.1×10^9	3.4×10^{38}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$1,024$	160	32	$1,024$	$10,240$	1.0×10^6	1.1×10^9	1.8×10^{308}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
2^{20}	320	1024	1.0×10^6	2.1×10^7	1.1×10^{12}	1.2×10^{18}	$6.7\times 10^{315,652}$

Careful!

- It's also true that the worst-case time is $O(N^2)$, since $N \in O(N^2)$ also: Big-Oh bounds are loose.
- The worst-case time is $\Omega(N)$, since $N \in \Omega(N)$, but that does *not* mean that the loop *always* takes time N, or even $K \cdot N$ for some K.
- Instead, we are just saying something about the *function* that maps N into the *largest possible* time required to process an array of length N.
- To say as much as possible about our worst-case time, we should try to give a Θ bound: in this case, we can: $\Theta(N)$.
- But again, that still tells us nothing about *best-case* time, which happens when we find `X` at the beginning of the loop. Best-case time is $\Theta(1)$.

Effect of Nested Loops

- Nested loops often lead to polynomial bounds:

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

- Clearly, time is $O(N^2)$, where $N =$ `A.length`. *Worst-case time* is $\Theta(N^2)$.
- Loop is inefficient though:

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

- Now worst-case time is proportional to

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

(so asymptotic time unchanged by the constant factor).

Recursion and Recurrences: Fast Growth

- Silly example of recursion:

```
/** True iff X is a substring of S */
boolean occurs (String S, String X) {
  if (S.equals (X)) return true;
  if (S.length () <= X.length () return false;
  return
    occurs (S.substring (1), X) ||
    occurs (S.substring (0, S.length ()-1), X);
}
```

- In the worst case, both recursive calls happen.
- Consider a fixed size for X, say N_0.
- Define $C(N)$ to be the worst-case cost of occurs(S,X) for S of length N, measured in # of calls to occurs. Then

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

- So $C(N)$ grows exponentially:

$$C(N) = 2C(N-1) = 2 \cdot 2C(N-2) = \ldots = \underbrace{2 \cdot 2 \cdots 2}_{N-N_0} \cdot 1 = 2^{N-N_0} \in \Theta(2^N)$$

Binary Search: Slow Growth

```
/** True X iff is an element of S[L .. U]. Assumes
 *  S in ascending order, 0 <= L <= U-1 < S.length. */
boolean isIn (String X, String[] S, int L, int U) {
  if (L > U) return false;
  int M = (L+U)/2;
  int direct = X.compareTo (S[M]);
  if (direct < 0) return isIn (X, S, L, M-1);
  else if (direct > 0) return isIn (X, S, M+1, U);
  else return true;
}
```

- Here, worst-case time, $C(D)$, (as measured by # of string comparisons), depends on size $D = U - L + 1$.
- We eliminate S[M] from consideration each time and look at half the rest. Assume $D = 2^k - 1$ for simplicity, so:

$$\begin{aligned} C(D) &= \begin{cases} 0, & \text{if } D \le 0, \\ 1 + C((D-1)/2), & \text{if } D > 0. \end{cases} \\ &= \underbrace{1 + 1 + \ldots + 1}_{k} + 0 \\ &= k = \lceil \lg D \rceil \in \Theta(\lg D) \end{aligned}$$

Another Typical Pattern: Merge Sort

```
List sort (List L) {
  if (L.length () < 2) return L;
  Split L into L0 and L1 of about equal size;
  L0 = sort (L0);  L1 = sort (L1);
  return Merge of L0 and L1
}
```

Merge ("combine into a single, ordered list") takes time proportional to size of its result.

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

$$\begin{aligned} C(N) &= \begin{cases} 1, & \text{if } N < 2; \\ 2C(N/2) + N, & \text{if } N \ge 2. \end{cases} \\ &= 2(2C(N/4) + N/2) + N \\ &= 4C(N/4) + N + N \\ &= 8C(N/8) + N + N + N \\ &= N \cdot 1 + \underbrace{N + N + \ldots + N}_{k=\lg N} \\ &= N + N \lg N \in \Theta(N \lg N) \end{aligned}$$

- In general, $\Theta(N \lg N)$ for arbitrary N (not just 2^k).

Amortization: Expanding Vectors

- When using array for expanding sequence, best to double size of array to grow it. Here's why.
- If array is size s, doubling its size and moving s elements to the new array takes time $\propto 2s$.
- Cost of inserting N items into array, doubling size as needed, starting with array size 1:

To Insert Item #	Resizing Cost	Cumulative Cost	Resizing Cost per Item	Array Size After Insertions
1	0	0	0	1
2	2	2	1	2
3 to 4	4	6	1.5	4
5 to 8	8	14	1.75	8
⋮	⋮	⋮	⋮	⋮
$2^m + 1$ to 2^{m+1}	2^{m+1}	$2^{m+2} - 2$	≈ 2	2^{m+1}

- If we spread out (*amortize*) the cost of resizing, we average about 2 time units on each item: "amortized insertion time is 2 units."
- So even though worst-case time for adding *one* element to array of N elements is $2N$, time to add N elements is $\Theta(N)$, *not* $\Theta(N^2)$.