CS61B Lecture #16: Complexity
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?
  - **Maintenance costs**: Upgrades, bug fixes.
  - **Costs of failure**: How robust? How safe?

- Is this program **fast enough**? Depends on:
  
  - For what purpose;
  - For 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 $10^8$ 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 100MB in \approx 50 sec.
  - I pick #2.

• In very many cases, almost anything will do: Keep It Simple.
Cost Measures (Time)

- **Wall-clock or execution time**
  - You can do this at home:
    \[
    \text{time java FindPrimes 1000}
    \]
  - 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.

- **Dynamic statement counts** of # of times 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 as functions 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 some results.
    * Times for small inputs not usually important.
    * Often more interested in asymptotic behavior as input size becomes very large.
  - *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 functions with similarly behaved magnitudes**.

• Then say something like “f is bounded by g if it is in g’s family.”

• For any function g(x), the functions 2g(x), 0.5g(x), or for any K > 0, K · 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 · 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.

• For upper limits, throw in all functions whose absolute value is everywhere ≤ some member of g’s family. Call this set O(g) or O(g(n)).

• Or, for lower limits, throw in all functions whose absolute values is everywhere ≥ some member of g’s family. Call this set Ω(g).

• Finally, define \( \Theta(g) = O(g) \cap \Omega(g) \)—the set of functions **bracketed in magnitude by** two members of g’s family.
Big Oh

- **Goal:** Specify bounding from above.

\[ M = 1 \]

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

- So \( f(x) \) is in \( g \)'s “bounded-above family,” written

\[ f(x) \in O(g(x)) , \]

- … even though (in this case) \( f(x) > g(x) \) everywhere.
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 "bounded-below family," written

\[
f'(x) \in \Omega(g(x)),
\]

... even though \( f(x) < g(x) \) everywhere.
Big Theta

• In the two previous slides, we not only have \( f(x) \in O(g(x)) \) and \( f'(x) \in \Omega(g(x)) \), ...

• ... but also \( f(x) \in \Omega(g(x)) \) and \( f'(x) \in O(g(x)) \).

• We can summarize this all by saying \( f(x) \in \Theta(g(x)) \) and \( f'(x) \in \Theta(g(x)) \).
Aside: Various Mathematical Pedantry

• Technically, if I am going to talk about $O(\cdot)$, $\Omega(\cdot)$ and $\Theta(\cdot)$ as sets of functions, I really should write, for example,

$$f \in O(g) \quad \text{instead of} \quad f(x) \in O(g(x))$$

• In effect, $f(x) \in O(g(x))$ is short for $\lambda x. f(x) \in O(\lambda x. g(x))$.

• The standard notation outside this course, in fact, is $f(x) = O(g(x))$, but personally, I think that’s a serious abuse of notation.
How We Use Order Notation

• Elsewhere in mathematics, you’ll see $O(\ldots)$, etc., used generally to specify bounds on functions.

• For example,

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

which I would prefer to write

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

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

• Also, you’ll see things like

$$f(x) = x^3 + x^2 + O(x) \quad \text{(or } f(x) \in x^4 + x^2 + O(x)),$$

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

• For our purposes, the functions we will be bounding will be cost functions: functions that measure the amount of execution time or the amount of space required by a program or algorithm.
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 matter, but at some point, constants always get swamped.

<table>
<thead>
<tr>
<th>$n$</th>
<th>$16 \log n$</th>
<th>$\sqrt{n}$</th>
<th>$n \log n$</th>
<th>$n^2$</th>
<th>$n^3$</th>
<th>$2^n$</th>
</tr>
</thead>
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<tr>
<td>2</td>
<td>16</td>
<td>1.4</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>4</td>
</tr>
<tr>
<td>4</td>
<td>32</td>
<td>2</td>
<td>4</td>
<td>8</td>
<td>16</td>
<td>64</td>
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<tr>
<td>8</td>
<td>48</td>
<td>2.8</td>
<td>8</td>
<td>24</td>
<td>64</td>
<td>512</td>
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<tr>
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<td>4</td>
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<td>64</td>
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<td>80</td>
<td>5.7</td>
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<td>160</td>
<td>1024</td>
<td>32,768</td>
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<tr>
<td>64</td>
<td>96</td>
<td>8</td>
<td>64</td>
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<td>4,096</td>
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<tr>
<td>128</td>
<td>112</td>
<td>11</td>
<td>128</td>
<td>896</td>
<td>16,384</td>
<td>$2.1 \times 10^9$</td>
</tr>
<tr>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
</tr>
<tr>
<td>$1,024$</td>
<td>160</td>
<td>32</td>
<td>$1,024$</td>
<td>10,240</td>
<td>$1.0 \times 10^6$</td>
<td>$1.1 \times 10^9$</td>
</tr>
<tr>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
<td>$\vdots$</td>
</tr>
<tr>
<td>$2^{20}$</td>
<td>320</td>
<td>1024</td>
<td>$1.0 \times 10^6$</td>
<td>$2.1 \times 10^7$</td>
<td>$1.1 \times 10^{12}$</td>
<td>$1.2 \times 10^{18}$</td>
</tr>
</tbody>
</table>
Some Intuition on Meaning of Growth

- How big a problem can you solve in a given time?
- In the following table, left column shows time in microseconds to solve a given problem as a function of problem size $N$.
- Entries show the size of problem that can be solved in a second, hour, month (31 days), and century, for various relationships between time required and problem size.
- $N = \text{problem size}$.

<table>
<thead>
<tr>
<th>Time ($\mu sec$) for problem size $N$</th>
<th>1 second</th>
<th>Max $N$ Possible in 1 hour</th>
<th>1 month</th>
<th>1 century</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\lg N$</td>
<td>$10^{300000}$</td>
<td>$10^{10000000000}$</td>
<td>$10^{8\cdot10^{11}}$</td>
<td>$10^{10^{14}}$</td>
</tr>
<tr>
<td>$N$</td>
<td>$10^6$</td>
<td>$3.6 \cdot 10^9$</td>
<td>$2.7 \cdot 10^{12}$</td>
<td>$3.2 \cdot 10^{15}$</td>
</tr>
<tr>
<td>$N \lg N$</td>
<td>63000</td>
<td>$1.3 \cdot 10^8$</td>
<td>$7.4 \cdot 10^{10}$</td>
<td>$6.9 \cdot 10^{13}$</td>
</tr>
<tr>
<td>$N^2$</td>
<td>1000</td>
<td>60000</td>
<td>$1.6 \cdot 10^6$</td>
<td>$5.6 \cdot 10^7$</td>
</tr>
<tr>
<td>$N^3$</td>
<td>100</td>
<td>1500</td>
<td>14000</td>
<td>150000</td>
</tr>
<tr>
<td>$2^N$</td>
<td>20</td>
<td>32</td>
<td>41</td>
<td>51</td>
</tr>
</tbody>
</table>
Using the Notation

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

```java
/** Find position of X in list L, or -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 ignore empty list.
Be 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 any array of length $N$.

• To say as much as possible about our worst-case time, we should try to give a $\Theta$ 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:

```java
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:

```java
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. In the worst case, both recursive calls happen:

```java
/** 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);
}
```

• Define $C(N)$ to be the worst-case cost of $\text{occurs}(S,X)$ for $S$ of length $N$, $X$ of fixed size $N_0$, measured in # of calls to $\text{occurs}$. Then

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

• So $C(N)$ grows exponentially:

$$C(N) = 2C(N - 1) + 1 = 2(2C(N - 2) + 1) + 1 = \ldots = 2^{\overbrace{\ldots 2 \cdot 1 + 1}^{N-N_0}} + \ldots + 1 = 2^{N-N_0+1} - 1 \in \Theta(2^N)$$
/** 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 calls to .compareTo),
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:

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

\[
= 1 + 1 + \ldots + 1 + 0
\]

\[
= k = \log(D + 1) \in \Theta(\log D)
\]
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 (which is proportional to # items merged):

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

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

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

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

$$= N \cdot 0 + \underbrace{N + N + \ldots + N}_{k=\lg N}$$

$$= N \lg N$$

• In general, can say it’s $\Theta(N \lg N)$ for arbitrary $N$ (not just $2^k$).