Today

• How to compare two algorithms?
• Analyzing code
• Big-Oh

Comparing Two Algorithms...

Comparing algorithms

When is one algorithm (not implementation) better than another?

• Various possible answers (clarity, security, …)
• But a big one is performance: for sufficiently large inputs, runs in less time (our focus) or less space

Large inputs (n) because probably any algorithm is “plenty good” for small inputs (if n is 10, probably anything is fast enough)!

Answer will be independent of CPU speed, programming language, coding tricks, etc.

Answer is general and rigorous, complementary to “coding it up and timing it on some test cases”

– Can do analysis before coding!
Analyzing code ("worst case")

Basic operations take "some amount of" constant time
- Arithmetic (fixed-width)
- Assignment
- Access one Java field or array index
- Etc.
(This is an approximation of reality, a very useful "lie".)

Consecutive statements
Conditionals
Loops
Calls
Recursion

Sum of times
Time of test plus slower branch
Sum of iterations
Time of call's body
Solve recurrence equation

Example

Find an integer in a sorted array

// requires array is sorted
// returns whether k is in array
boolean find(int[] arr, int k) {
    ?
}

Best case:
Worst case:

Best case: 6ish steps = O(1)
Worst case: 6ish*(arr.length) = O(arr.length)

Binary search

Find an integer in a sorted array
- Can also be done non-recursively but "doesn't matter" here

Best case: 8ish steps = O(1)
Worst case: \( \frac{10n}{2} + \frac{n}{2} \) where \( n \) is hi-lo
- \( O(\log n) \) where \( n \) is array length
- Solve recurrence equation to know that...

Linear search

Find an integer in a sorted array

// requires array is sorted
// returns whether k is in array
boolean find(int[] arr, int k) {
    for(int i=0; i < arr.length; ++i)
        if(arr[i] == k)
            return true;
    return false;
}

Best case: 6ish steps = O(1)
Worst case: 6ish*(arr.length) = O(arr.length)
Solving Recurrence Relations

1. Determine the recurrence relation. What is the base case?
   \[ T(n) = 10 + T\left(\frac{n}{2}\right) \]
   \[ T(1) = 8 \]

2. “Expand” the original relation to find an equivalent general expression in terms of the number of expansions.
   \[ T(n) = 10k + T\left(\frac{n}{2^k}\right) \]

3. Find a closed-form expression by setting the number of expansions to a value which reduces the problem to a base case.
   \[ \frac{n}{2^k} = 1 \Rightarrow n = 2^k \]
   \[ k = \log_2 n \]
   \[ T(n) = 10 \log_2 n + 8 \]

Ignoring constant factors

- So binary search is \( O(\log n) \) and linear is \( O(n) \)
  - But which is faster
- Could depend on constant factors
  - How many assignments, additions, etc. for each \( n \)
  - And could depend on size of \( n \)
- But there exists some \( n_0 \) such that for all \( n > n_0 \) binary search wins
- Let’s play with a couple plots to get some intuition...

Another example: sum array

Two “obviously” linear algorithms: \( T(n) = O(1) + T(n-1) \)

Iterative:
```java
int sum(int[] arr) {
    int ans = 0;
    for (int i = 0; i < arr.length; ++i) {
        ans += arr[i];
    }
    return ans;
}
```

Recursive:
```java
int sum(int[] arr) {
    return help(arr, 0, arr.length);
}
```
```java
int help(int[] arr, int lo, int hi) {
    if (lo == hi) return 0;
    if (lo == hi-1) return arr[lo];
    int mid = (hi+lo)/2;
    return help(arr, lo, mid) + help(arr, mid, hi);
}
```

What about a binary version?

```java
int sum(int[] arr) {
    return help(arr, 0, arr.length);
}
```
```java
int help(int[] arr, int lo, int hi) {
    if (lo == hi) return 0;
    if (lo == hi-1) return arr[lo];
    int mid = (hi+lo)/2;
    return help(arr, lo, mid) + help(arr, mid, hi);
}
```

Recurrence is \( T(n) = O(1) + 2T\left(\frac{n}{2}\right) \)
- \( 1 + 2 + 4 + 8 + \ldots \) for \( \log n \) times
- \( 2\log_2 n - 1 \) which is proportional to \( n \) (definition of logarithm)
Easier explanation: it adds each number once while doing little else
“Obvious”: You can’t do better than \( O(n) \) – have to read whole array

Example

- Let’s try to “help” linear search
  - Run it on a computer 100x as fast (say 2010 model vs. 1990)
  - Use a new compiler/language that is 3x as fast
  - Be a clever programmer to eliminate half the work
- So doing each iteration is 600x as fast as in binary search
- Note: 600x still helpful for problems without logarithmic algorithms!
Parallelism teaser

• But suppose we could do two recursive calls at the same time
  – Like having a friend do half the work for you!

```java
int sum(int[] arr) {
    return help(arr, 0, arr.length);
}

int help(int[] arr, int lo, int hi) {
    if(lo==hi) return 0;
    if(lo==hi-1) return arr[lo];
    int mid = (hi+lo)/2;
    return help(arr, lo, mid) + help(arr, mid, hi);
}
```

• If you have as many “friends of friends” as needed, the recurrence is now
  \[ T(n) = O(1) + 1 \cdot T(n/2) \]

Really common recurrences

Should know how to solve recurrences but also recognize some really common ones:

- \[ T(n) = O(1) + T(n-1) \quad \text{linear} \]
- \[ T(n) = O(1) + 2 \cdot T(n/2) \quad \text{O}(n \log n) \]
- \[ T(n) = O(1) + T(n/2) \quad \text{logarithmic} \]
- \[ T(n) = O(1) + 2 \cdot T(n/2) \quad \text{linear} \]
- \[ T(n) = O(n) + T(n/2) \quad \text{linear} \]
- \[ T(n) = O(n^2) + T(n/2) \quad \text{O}(n \log n) \]
- \[ T(n) = O(n^5) + T(n/2) \quad \text{exponential} \]

Asymptotic notation

About to show formal definition, which amounts to saying:

1. Eliminate low-order terms
2. Eliminate coefficients

Examples:

- \[ 4n + 5 \rightarrow O(n) \]
- \[ 0.5n \log n + 2n + 7 \rightarrow O(n \log n) \]
- \[ n \log 10^2 \rightarrow O(n) \]

Examples

True or false?

1. \[ 4n + 3n \] is \( O(n) \) \quad True
2. \[ n + 2 \log n \] is \( O(\log n) \) \quad False
3. \[ \log n + 2 \] is \( O(1) \) \quad False
4. \[ n^{50} \] is \( O(1.1^n) \) \quad True

Notes:

• Do NOT ignore constants that are not multipliers:
  – \( n^3 \) is \( O(n^2) \) : FALSE
  – \( 3^5 \) is \( O(2^n) \) : FALSE
• When in doubt, refer to the definition

Big-Oh relates functions

We use \( O \) on a function \( f(n) \) (for example \( n^2 \)) to mean the set of functions with asymptotic behavior less than or equal to \( f(n) \)

So \( (3n^2 + 17) \) is in \( O(n^2) \)

Confusingly, we also say/write:

- \( 3n^2 + 17 \) and \( n^2 \) have the same asymptotic behavior
- \( (3n^2 + 17) \) is \( O(n^2) \)
- \( (3n^2 + 17) \) is \( O(n^3) \)

But we would never say \( O(n^2) = (3n^2 + 17) \)

Formally Big-Oh

Definition: \( g(n) \) is in \( O(f(n)) \) if and only if there exist positive constants \( c \) and \( n_0 \) such that

\[
g(n) \leq c \cdot f(n) \quad \text{for all } n \geq n_0
\]

To show \( g(n) \) is in \( O(f(n)) \), pick a \( c \) large enough to "cover the constant factors" and \( n_0 \) large enough to "cover the lower-order terms";

• Example: Let \( g(n) = 3n^2 + 17 \) and \( f(n) = n^2 \)
  
  \( c = 5 \) and \( n_0 = 10 \) is more than good enough

This is "less than or equal to";

- \( 3n^2 + 17 \) is also \( O(n^2) \) and \( O(2^n) \) etc.
Using the definition of Big-Oh (Example 1)

For \( g(n) = 4n + f(n) - n^2 \), prove \( g(n) \) is in \( O(f(n)) \)
- A valid proof is to find valid \( c \) & \( n_0 \)
- When \( n=4 \), \( g(4) = 16 \) & \( f(4) = 16 \); this is the crossing over point.
- So we can choose \( n_0 = 4 \), and \( c = 1 \)
- Note: There are many possible choices: ex: \( n_0 = 78 \), and \( c = 42 \) works fine.

The Definition: \( g(n) \) is in \( O(f(n)) \) if there exist positive constants \( c \) and \( n_0 \) such that \( g(n) \leq c f(n) \) for all \( n \geq n_0 \).

Using the definition of Big-Oh (Example 2)

For \( g(n) = n^2 \) & \( f(n) = 2n \), prove \( g(n) \) is in \( O(f(n)) \)
- A valid proof is to find valid \( c \) & \( n_0 \)
- One possible answer: \( n_0 = 20 \), and \( c = 1 \)

The Definition: \( g(n) \) is in \( O(f(n)) \) if there exist positive constants \( c \) and \( n_0 \) such that \( g(n) \leq c f(n) \) for all \( n \geq n_0 \).

What's with the \( c \)?

- To capture this notion of similar asymptotic behavior, we allow a constant multiplier (called \( c \)).
- Consider: \( g(n) = 7n+5 \)
  \( f(n) = n \)
  - These have the same asymptotic behavior (linear), so \( g(n) \) is in \( O(f(n)) \) even though \( g(n) \) is always larger.
  - There is no positive \( n_0 \), such that \( g(n) \leq f(n) \) for all \( n \geq n_0 \).
  - The \( c \) in the definition allows for that:
    \( g(n) \leq c f(n) \) for all \( n \geq n_0 \).
  - To prove \( g(n) \) is in \( O(f(n)) \), have \( c = 12 \), \( n_0 = 1 \).

Big Oh: Common Categories

From fastest to slowest:
\( O(1) \) constant (same as \( O(k) \) for constant \( k \))
\( O(\log n) \) logarithmic
\( O(n) \) linear
\( O(n \log n) \) \( \theta(n \log n) \)
\( O(n^2) \) quadratic
\( O(n^k) \) cubic
\( O(k^n) \) polynomial (where \( k \) is an constant)
\( O(k^n) \) exponential (where \( k \) is any constant \( >1 \)).

Usage note: “exponential” does not mean “grows really fast”!
It means “grows at rate proportional to \( k^2 \) for some \( k >1 \)”

More Asymptotic Notation

- Upper bound: \( \Theta(f(n)) \) is the set of all functions asymptotically less than or equal to \( f(n) \)
  - \( g(n) \) is in \( \Theta(f(n)) \) if there exist constants \( c \) and \( n_0 \) such that \( g(n) \leq c f(n) \) for all \( n \geq n_0 \).

- Lower bound: \( \Omega(f(n)) \) is the set of all functions asymptotically greater than or equal to \( f(n) \)
  - \( g(n) \) is in \( \Omega(f(n)) \) if there exist constants \( c \) and \( n_0 \) such that \( g(n) \geq c f(n) \) for all \( n \geq n_0 \).

- Tight bound: \( \Omega(f(n)) \) is the set of all functions asymptotically equal to \( f(n) \)
  - Intersection of \( \Theta(f(n)) \) and \( \Omega(f(n)) \) (use different \( c \) values)

Regarding use of terms

A common error is to say \( O(f(n)) \) when you mean \( \Theta(f(n)) \)
- People often say \( O() \) to mean a tight bound
- Say we have \( f(n)=n \); we could say \( f(n) \) is in \( O(n) \), which is true, but only conveys the upper-bound.
- Since \( f(n)=n \) is also \( \Omega(n) \), it’s tempting to say this algorithm is exactly \( O(n) \).
- Somewhat incomplete; instead say it is \( \Theta(n) \)
- That means that it is not, for example \( O(\log n) \)

Less common notation:
- “little-oh”: like “big-Oh” but strictly less than
  - Example: sum is \( k^2 \) but not \( o(n) \)
- “little-omega”: like “big-Omega” but strictly greater than
  - Example: sum is \( \omega(\log n) \) but not \( o(n) \)
**What we are analyzing**

- The most common thing to do is give an $O$ or $\Theta$ *bound* to the worst-case running time of an algorithm
- Example: True statements about binary-search algorithm
  - Common: $\Theta(\log n)$ running time in the worst-case
  - Less common: $\Theta(1)$ in the best-case (item is in the middle)
  - Less common: Algorithm is $\Omega(\log \log n)$ in the worst-case (it is not really, really, really fast asymptotically)
  - Less common (but very good to know): the find-in-sorted-array problem is $\Omega(\log n)$ in the worst-case
  - No algorithm can do better (without parallelism)
  - A problem cannot be $\Theta(n/\log n)$ since you can always find a slower algorithm, but can mean there exists an algorithm

**Other things to analyze**

- Space instead of time
  - Remember we can often use space to gain time
- Average case
  - Sometimes only if you assume something about the distribution of inputs
  - See CSE312 and STAT391
  - Sometimes uses randomization in the algorithm
  - Will see an example with sorting; also see CSE312
  - Sometimes an amortized guarantee
  - Will discuss in a later lecture

**Summary**

Analysis can be about:

- The problem or the algorithm (usually algorithm)
- Time or space (usually time)
  - Or power or dollars or ...
- Best-, worst-, or average-case (usually worst)
- Upper-, lower-, or tight-bound (usually upper or tight)

**Big-Oh Caveats**

- Asymptotic complexity (Big-Oh) focuses on behavior for *large* $n$
  - and is independent of any computer / coding trick
  - Example: $n^{10} \text{ vs. } \log n$
  - Asymptotically $n^{10}$ grows more quickly
  - But the “cross-over” point is around $5 \times 10^{17}$
  - So if you have input size less than $2^{58}$, prefer $n^{10}$
- Comparing $O()$ for *small* $n$ values can be misleading
  - Quicksort: $O(n \log n)$ (expected)
  - Insertion Sort: $O(n^2)$ (expected)
  - Yet in reality Insertion Sort is faster for small n's
  - We'll learn about these sorts later

**Addendum: Timing vs. Big-Oh?**

- At the core of CS is a backbone of theory & mathematics
  - Examine the algorithm itself, mathematically, not the implementation
  - Reason about performance as a function of $n$
  - Be able to mathematically prove things about performance
- Yet, timing has its place
  - In the real world, we do want to know whether implementation A runs faster than implementation B on data set C
  - Ex: Benchmarking graphics cards
  - We will do some timing in project 3 (and in 2, a bit)
- Evaluating an algorithm? Use asymptotic analysis
- Evaluating an implementation of hardware/software? Timing can be useful