

CSE 332

Data Structures & Parallelism

Algorithm Analysis

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Spring 2024

Today & Next Time - Algorithm Analysis

- What do we care about?
- How to compare two algorithms
- Analyzing code
- Asymptotic Analysis
- Big-Oh Definition

What do we care about?

- Correctness:
 - Does the algorithm do what is intended.
- Performance:
 - Speed time complexity
 - Memory space complexity
- Why analyze?
 - To make good design decisions
 - Enable you to look at an algorithm (or code) and identify the bottlenecks, etc.

Q: How should we compare two algorithms?
Sort all students who have taken 332

Chandni

Arya

5 seconds

4 seconds

3.5 seconds

2 seconds

0 seconds

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A: How should we compare two algorithms?

- Uh, why NOT just run the program and time it??
 - Too much **variability**, not reliable or **portable**:
 - Hardware: processor(s), memory, etc.
 - OS, Java version, libraries, drivers
 - Other programs running
 - Implementation dependent
- Choice of input
 - Testing (inexhaustive) may **miss** worst-case input
 - Timing does not **explain** relative timing among inputs (what happens when n doubles in size)
- Often want to evaluate an **algorithm**, not an implementation
 - Even **before** creating the implementation (“coding it up”)

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!

Goals for Algorithm Analysis

- Identify a function which maps the algorithm's input size to a measure of resources used
 - Input of the function: **size of the function input (n)**
 - Number of characters in a string, number of items in a list, number of pixels in an image
 - Output of the function: **counts of resources used**
- Important note: Make sure you know the “units” of your domain and codomain!

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 - **How to count different code constructs**
 - Best Case vs Worst Case
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Analyzing code

Basic operations take “some amount of” constant time

- Arithmetic
- Assignment
- Access one Java field or array index
- Etc.



(This is an *approximation of reality*: a very useful “lie”.)

Consecutive statements

Sum of time of each statement

Loops

Num iterations * time for loop body

Conditionals

Time of condition plus time of slower branch

Function Calls

Time of function's body

Recursion

Solve recurrence equation

Example 1

```
b = b + 5  
c = b / a  
b = c + 100
```

```
for (i = 0; i < n; i++) {  
    sum++;  
}
```

```
if (j < 5) {  
    sum++;  
} else {  
    for (i = 0; i < n; i++) {  
        sum++;  
    }  
}
```

$5n+1$

$5n+1$

$5n+2$

Example 2

```
int coolFunction(int n, int sum) {  
    int i, j;  
    for (i = 0; i < n; i++) {  
        for (j = 0; j < n; j++) {  
            sum++;  
        }  
    }  
    print "This program is great!"  
    for (i = n; i > 1; i = i / 2) {  
        sum++;  
    }  
    return sum  
}
```

$24n^2$

$5 \log n + 1$

1

Using Summation for Loops

```
for (i = 0; i < n; i++) {  
    sum++;  
}
```

$$\sum_{i=0}^{n-1} 5 = 5n$$

Example 3

```
List<Integer> beAnnoying(List<Integer> lst) {  
    List m = new ArrayList<Integer>();  
    for (i = 0; i < lst.size(); i++){  
        m.add(lst.get(i));  
        for (j = 0; j < lst.size(); j++){  
            print("Hi, I'm annoying");  
        }  
    }  
    return m;  
}
```

What about memory?

```
List<Integer> beAnnoying(List<Integer> lst) {  
    List m = new ArrayList<Integer>();  
    for (i = 0; i < lst.size(); i++) {  
        m.add(lst.get(i));  
        for (j = 0; j < lst.size(); j++) {  
            print("Hi, I'm annoying");  
        }  
    }  
    return m;  
}
```

$$5n^2 + 3n$$

$$\sum_{i=0}^{n-1} \left(\sum_{j=0}^{n-1} 5 + 3 \right)$$

$O(n^2)$

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Complexity cases

We'll start by focusing on two scenarios:

- Worst-case complexity: max # steps algorithm takes on “most challenging” input of size N
- Best-case complexity: min # steps algorithm takes on “easiest” input of size N

Example - best case? worst case?

```
b = b + 5  
c = b / a  
b = c + 100
```

constant

```
for (i = 0; i < n; i++) {  
    sum++;  
}
```

← 3

```
if (j < 5) {  
    sum++;  
} else {  
    for (i = 0; i < n; i++) {  
        sum++;  
    }  
}
```

←

Example

5	8	13	42	75	79	88	90	95	99
0	1	2	3	4	5	6	7	8	9

Find an integer in a *sorted array*

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

Linear search - Best Case & Worst Case

5	8	13	42	75	79	88	90	95	99
0	1	2	3	4	5	6	7	8	9

```
// 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:

Worst case:

Linear search - Best Case & Worst Case

5	8	13	42	75	79	88	90	95	99
0	1	2	3	4	5	6	7	8	9

```
// 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: 6-ish steps = $O(1)$

Worst case:

5-ish steps * (arr.length) = $O(n)$

Remember a faster search algorithm?

binary

$\log n$

linear

n

Worst case analysis

- Worst-case complexity: max # steps algorithm takes on “most challenging” input of size N
 - Does NOT depend on how big N is
 - Depends on the actual arguments to the algorithm

Today - Algorithm Analysis

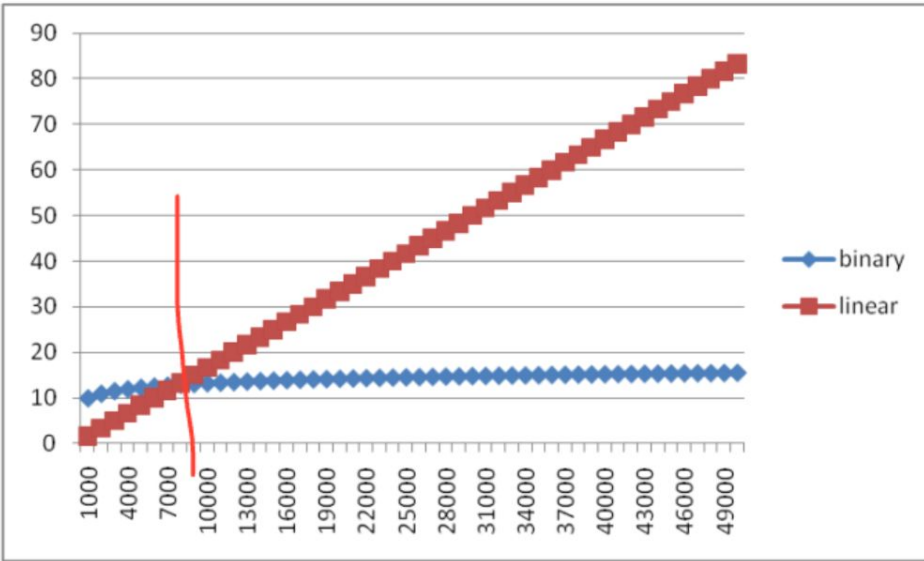
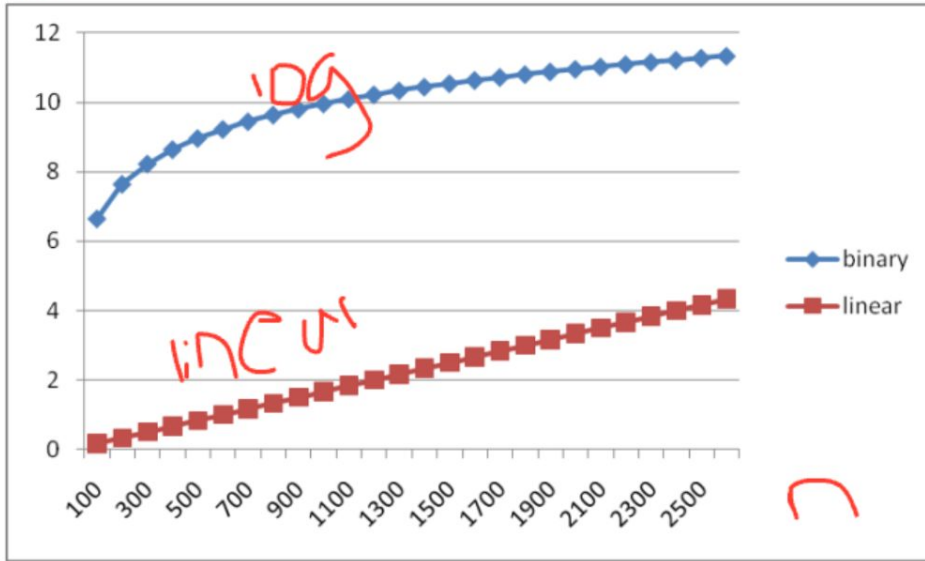
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Ignoring constant factors

- So binary search is $O(\log n)$ and linear is $O(n)$
 - But which will actually be faster?
 - Depending on **constant factors** and **size of n** ; in a particular situation, **linear search could be faster**....
- Could depend on constant factors
 - How *many* assignments, additions, etc. for each n
- And could depend on size of n – what if n is small?
- **But** there exists some n_0 such that for all $n > n_0$ **binary search “wins”**
- Let's look at a couple plots to get some intuition...

Linear search vs Binary search

time



Let's give linear search a boost ($n / 600$)