

 Lec\_34.md

# Lecture 34

Dec. 03/2020

## Announcements

### Quiz 7

- Monday, December 7th, 2020
- 25 Minutes in duration
- Take at any time in the day
  - Don't start later than 12:35
- Covers all the material
  - Up to Lab 4

## Complexity Analysis

Recall that **execution time** of a program depends on

1. Size of the input  $n$
2. Input itself (data in the array w.r.t  $t$ )
  - `if(a[i]<t) count = count+1;` only runs depending on values of `a[i]` and `t`
3. Hardware/Compiler optimization
4. Steps run by program (algorithm)

## Define a Step

A **step** is an instruction/operation that takes a *constant* amount of time

- **step** runtime is independent of the size of the problem (e.g.  $n$ )

## Execution Time

We've reduced the measurement of execution time from a unit in seconds

- To a unit of **step's**

## Example 1

```
count = 0;
for(int i = 0; i < n; i++){
    count = count + 1;
}
cout << count;
```

Notes:

1. This loop has no dependence on input data

- So  $T_{best} = T_{worst} = T_{avg}$

## Example 2

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```
int count = 0;
for(i = 0; i < n; i++){
    if(a[i]<t) count = count+1;
}
cout << count;
```

Notes:

1. Let  $c$  be the steps inside the for loop
2. Let  $d$  be the steps outside the for loop
3. Best Case

- $T_{best} = c*n + d$ 
  - Only one step inside the for loop (if)

4. Worst Case

- $T_{worst} = (c+1)*n + d$ 
  - Two steps inside the for loop (if and assign)

5. Average Case

- $T_{avg} = (c+0.5)*n + d$ 
  - Mean between best case scenario and worst case scenario

## Time Complexity

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If  $n$  is small

- 5, 10, 100

Then the difference between magnitudes of different time complexity orders is small anyways

- For case  $1000*n$ :  $1000*50 \text{ uS} = 0.05 \text{ S}$
- For case  $2^n$ :  $2^{50} \text{ uS} = 0.25 \text{ S}$

But *only* when  $n$  is really large do the differences between algorithm runtime start to show

- Look at how a function runtime *grows* as the value  $n$  is scaled up
- For case  $1000*n$ :  $1000*1000 \text{ uS} = 1 \text{ S}$
- For case  $2^n$ :  $2^{1000} \text{ uS} = 3.4*10^{286} \text{ centuries}$

So look at how algorithm runtime changes based on size of input  $n$  - since large  $n$ 's are the only place differences in speed actually show

## Asymptotic Behaviour

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The execution time  $T(n)$  is said to be  $O(g(n))$ , denoted as  $T(n)=O(g(n))$  if there exists a constant  $c$  and a value of  $n=n_0$  such that

- $T(n) \leq c * g(n)$
- $n \geq n_0$

# Big-O Notation

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$O(g(n))$  , or **Big-O Notation** represents the *order* of a function's runtime

- Can separate classes into **complexity classes**

Common categories:

1.  $O(1)$ 
  - This is rare
  - Same runtime regardless of how large the size of the input is
2.  $O(\log n)$ 
  - Great algorithms
3.  $O(n)$ 
  - Linear algorithms
4.  $O(n \log n)$ 
  - Somewhere between linear and n-squared
5.  $O(n^2)$ 
  - Polynomial growth
6.  $O(n^3)$
7.  $O(2^n)$

Two more just for fun:

8.  $O(n!)$ 
  - The dreaded "factorial time"
9.  $O(n^n)$ 
  - There is something really wrong if your algorithm is here

## Big O Notation Examples

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```
for (i=0 ; i < n ; ++i) {  
    O(1)  
}
```

Notes:

1. The  $O(1)$  just represents that each step in the for loop runs in constant time
  - Think about an assign statement, like `int x = 0;`
2. This is  $O(n)$  time

```

for (i=0 ; i < n ; ++i) {
    for (j=0 ; j < n ; ++j) {
        O(1)
    }
}

```

Notes:

1. This is  $O(n^2)$
- Two nested for loops
  - The inside for loop runs  $n$  times for each run of the outer loop
  - Therefore time complexity should be of order  $n*n$

```

for (i=0 ; i < n ; ++i) {
    c[i][j] = 0;
    for (j=0 ; j < n ; ++j) {
        for (k=0; k < n ; ++k) {
            c[i][j] = c[i][j] + b[i][k] * a[k][j];
        }
    }
}

```

Notes:

1. This is  $O(n^3)$
- Three nested for loops
- Best, worst, and average is  $O(n^3)$

```

for (i=0 ; i < n ; ++i) {
    for (j=0 ; j < i ; ++j) {
        O(1)
    }
}

```

Notes:

1. Notice the second for loop has condition  $j < i$ 
  - $i$  is not a constant
    - $i$  depends on  $n$ , the size of the problem
2. So the execution time of the outer loop is  $0*c+1*c+2*c+3*c+4*c+5*c+\dots+(n-1)*c$ 
  - Where  $c$  is a constant
  - Look up triangular sum
  - $(n)*(n-1)/2$  runtime
    - Which is  $O(n^2)$
3. Order  $O(n^2)$

```

j = n;
do {
    O(1)
    j = j/2; // integer division
} while (j > 0)

```

1. This code involves repeated division by 2

- That's sort of similar to  $\log_n$
- In fact, this code is of order  $O(\log_n)$