

CSE 250

Data Structures

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Day 07

Runtime Analysis with Examples

Textbook Ch. 7.3-7.4

Announcements

- I'm back (obviously...)
- PA1 due on Friday at 11:59pm
 - Be wary of availability after 5:00pm...

Recap of Runtime Complexity

Big- Θ

- Growth functions are in the **same** complexity class
- If $f(n) \in \Theta(g(n))$ then an algorithm taking $f(n)$ steps is as "exactly" as fast as one that takes $g(n)$ steps.

Big-O

- Growth functions in the **same or smaller** complexity class.
- If $f(n) \in O(g(n))$, then an algorithm that takes $f(n)$ steps is *at least as fast* as one taking $g(n)$ (but it may be even faster).

Big- Ω

- Growth functions in the **same or bigger** complexity class
- If $f(n) \in \Omega(g(n))$, then an algorithm that takes $f(n)$ steps is *at least as slow* as one that takes $g(n)$ steps (but it may be even slower)

Recap of Runtime Complexity

Big- Θ – Tight Bound

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- If $f(n) \in \Theta(g(n))$ then an algorithm taking $f(n)$ steps is as "exactly" as fast as one that takes $g(n)$ steps.

Big-O – Upper Bound

- Growth functions in the **same or smaller** complexity class.
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Big- Ω – Lower Bound

- Growth functions in the **same or bigger** complexity class
- If $f(n) \in \Omega(g(n))$, then an algorithm that takes $f(n)$ steps is *at least as slow* as one that takes $g(n)$ steps (but it may be even slower)

Common Runtimes (in order of complexity)

Constant Time: $\Theta(1)$

Logarithmic Time: $\Theta(\log(n))$

Linear Time: $\Theta(n)$

Quadratic Time: $\Theta(n^2)$

Polynomial Time: $\Theta(n^k)$ for some $k > 0$

Exponential Time: $\Theta(c^n)$ (for some $c \geq 1$)

Common Runtimes (in order of complexity)

Constant Time: $\Theta(1)$

$$T(n) = c$$

Logarithmic Time: $\Theta(\log(n))$

$$T(n) = c \log(n)$$

Linear Time: $\Theta(n)$

$$T(n) = c_1 n + c_0$$

Quadratic Time: $\Theta(n^2)$

$$T(n) = c_2 n^2 + c_1 n^1 + c_0$$

Polynomial Time: $\Theta(n^k)$ for some $k > 0$

$$T(n) = c_k n^k + \dots + c_1 n + c_0$$

Exponential Time: $\Theta(c^n)$ (for some $c \geq 1$)

$$T(n) = c^n$$

Constants vs Asymptotics

Given the following pseudocode:

```
for (i ← 0 until n) { /* do work */ }
```

If the `/* do work */` portion of the code originally takes 10 steps...

But we optimize it to now take 7 steps...

Our total runtime goes from $10n$ steps to $7n$ steps: 30% faster!

...but still $\Theta(n)$

c and n_0

Compare the two runtimes:

$$T_1(n) = 100n$$

$$T_2(n) = n^2$$

- $100n = O(n^2)$ (T_2 is the slower runtime)
- ...but $c_{high} = 1, n_0 = 100$
- Until our input size reaches 100 or more, T_2 is the **faster** runtime

Takeaways

Asymptotically slower runtimes *can* be better in real-world situations.

- An algorithm with runtime T_2 is better on small inputs
- An algorithm with runtime T_2 might be easier to implement/maintain
- An algorithm with runtime T_1 might not exist

Takeaways

Asymptotically slower runtimes *can* be better in real-world situations.

- An algorithm with runtime T_2 is better on small inputs
- An algorithm with runtime T_2 might be easier to implement/maintain
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(sometimes this is provable...see CSE 331)

Takeaways

The important thing is learning the tools to *reason* about the different algorithms and *why* you might choose one over the other!

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The important thing is learning the tools to *reason* about the different algorithms and *why* you might choose one over the other!

...But for this class, we can assume that if $T_2(n)$ is in a bigger complexity class, then $T_1(n)$ is better/faster/stronger.

Now some examples...
...and common pitfalls

Bubble Sort

```
bubblesort(seq: Seq[Int]):  
1.  n ← seq length  
2.  for i ← n-2 to 0, by -1:  
3.    for j ← i to n-1:  
4.      if seq(j+1) < seq(j):  
5.        swap seq(j) and seq(j+1)
```

What is the runtime complexity class for bubblesort?

Helpful Summation Rules

$$1. \sum_{i=j}^k c = (k - j + 1)c$$

$$2. \sum_{i=j}^k (cf(i)) = c \sum_{i=j}^k f(i)$$

$$3. \sum_{i=j}^k (f(i) + g(i)) = \left(\sum_{i=j}^k f(i)\right) + \left(\sum_{i=j}^k g(i)\right)$$

$$4. \sum_{i=j}^k (f(i)) = \left(\sum_{i=\ell}^k (f(i))\right) - \left(\sum_{i=\ell}^{j-1} (f(i))\right) \text{ (for any } \ell < j)$$

$$5. \sum_{i=j}^k f(i) = f(j) + f(j+1) + \dots + f(k-1) + f(k)$$

$$6. \sum_{i=j}^k f(i) = f(j) + \dots + f(\ell-1) + \left(\sum_{i=\ell}^k f(i)\right) \text{ (for any } j < \ell \leq k)$$

$$7. \sum_{i=j}^k f(i) = \left(\sum_{i=j}^{\ell} f(i)\right) + f(\ell+1) + \dots + f(k) \text{ (for any } j \leq \ell < k)$$

$$8. \sum_{i=1}^k i = \frac{k(k+1)}{2}$$

$$9. \sum_{i=0}^k 2^i = 2^{k+1} - 1$$

10. $n! \leq c_s n^n$ is a tight upper bound (Sterling: Some constant c_s exists)

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Note: We can ignore the exact number of steps required by a portion of the algorithm, as long as we know its complexity...

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Lines 4-5 are executed exactly $n-1$ times, but we can treat this as $O(n)$ steps for the inner loop...or can we...?

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What is the complexity of this step?

Do not assume function calls take $O(1)$ time!

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Bubble Sort on Mutable Data

```
def sort(seq: mutable.Seq[Int]): Unit = {  
  val n = seq.length  
  for(i <- n - 2 to 0 by -1; j <- i to n) {  
    if(seq(n) < seq(j)) {  
      val temp = seq(j+1)  
      seq(j+1) = seq(j)  
      seq(j) = temp  
    }  
  }  
}
```

Bubble Sort on Immutable Data

```
def sort(seq: Seq[Int]): Seq[Int] = {  
  val newSeq = seq.toArray  
  val n = seq.length  
  for(i <- n - 2 to 0 by -1; j <- i to n) {  
    if(newSeq(n) < newSeq(j)) {  
      val temp = newSeq(j+1)  
      newSeq(j+1) = newSeq(j)  
      newSeq(j) = temp  
    }  
  }  
  return newSeq.toList  
}
```

Searching Sequences

```
def indexOf[T](seq: Seq[T], value: T, from: Int): Int = {  
  for(i <- from until seq.length) {  
    if(seq(i).equals(value)) { return i }  
  }  
  return -1  
}
```

What is the complexity?

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  return -1  
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```

What is the complexity? $O(n)$

Searching Sequences

```
def count[T](seq: Seq[T], value: T): Int = {  
  var count = 0;  
  var i = indexOf(seq, value, 0)  
  while(i != -1) {  
    count += 1;  
    i = indexOf(seq, value, i+1)  
  }  
  return count  
}
```

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What is the complexity? $O(n)$? What about this line? How many while iterations?

Searching Sequences

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```

What is the complexity? Each element is only checked once, so $O(n)$.

Searching Sorted Sequences

- Assuming $O(1)$ access to elements ('random access')
 - Divide the set of elements in half by taking the "middle" element, m
 - If m is greater than what we are looking for, search the lower half
 - If m is less than what we are looking for, search the right half
 - Repeat until you've found the element or you can't divide in half

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If you have n elements, how many times can you divide n in half?

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$\log(n)$