Time Complexity of function that contains another function

Asked 3 years, 6 months ago Modified 3 years, 6 months ago Viewed 565 times



Can someone meticulously explain how do I figure out the time complexity of this code?

```
{
    int sum = 0;
    while (n>1)
    {
        sum +=g(n)
        n = sqrt(n)
    }
    return sum;
```

int f(int n)

where g(n) is given by:

```
int g(int n)
{
    int sum = 0;
    for (int i = 1; i<n; i*=2)
        sum +=i;
    return sum;
}</pre>
```

Thanks in advance!

```
for-loop time while-loop complexity-theory
```

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edited Aug 29, 2018 at 11:52

Amadan

176k 19 214 272

asked Aug 29, 2018 at 11:37

Ron73404

21 3

3 Answers



A slightly more concrete way of proving the result:

As a previous answer correctly stated, the complexity of g(n) is $O(\log n)$. The precise number of times the loop in g(n) executes is floor(log2(n)) + 1.



Now for f(n). The value of n after the m-th iteration of the loop, with respect to the *original* value of n, is:

$$n_0 = n$$

$$n_1 = \sqrt{n}$$
 $= n^{\frac{1}{2}}$

$$n_2 = \sqrt{\sqrt{n}} = n^{\frac{1}{2^2}}$$

$$n_1 = \sqrt{n}$$
 $= n^{\frac{1}{2}}$
 $n_2 = \sqrt{\sqrt{n}}$ $= n^{\frac{1}{2^2}}$
 $n_3 = \sqrt{\sqrt{\sqrt{n}}}$ $= n^{\frac{1}{2^3}}$

$$n_m = n^{\frac{1}{2^m}}$$

From this, using the loop condition n > 1, the number of times this loop executes is:

$$m = \lfloor \log_2 \log_2 n \rfloor$$

This allows one to express the complexity function of f(n) as a summation:

$$T(n) = \sum_{m=0}^{\lfloor \log_2 \log_2 n \rfloor} \left(\left\lfloor \log_2 n^{\frac{1}{2^m}} \right\rfloor + 1 \right)$$

$$= \sum_{m=0}^{\lfloor \log_2 \log_2 n \rfloor} \left(\frac{1}{2^m} \log_2 n + O(1) + 1 \right) \tag{*}$$

$$= \log_2 n \times \sum_{m=0}^{\log_2 \log_2 n + O(1)} \frac{1}{2^m} + O(\log \log n)$$

$$= \log_2 n \times \frac{1 - 2^{-\log_2 \log_2 n + O(1)}}{1 - \frac{1}{2}} + O(\log \log n) \tag{**}$$

In (*) I used the fact that a number rounded down only differs from its original value by less than 1 (hence o(1)). In (**) I used the standard result for geometric series sums.

The underlined term in (**) has a negative power of 2. When n tends to infinity, this term vanishes, so the underlined term itself converges to 2.

Therefore the final complexity is just $O(\log n + \log \log n) = O(\log n)$, since the first term dominates.

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answered Aug 29, 2018 at 12:30



meowgoesthedog
13.9k 4 23 36



g is logarithmic on its arguments (if you pass it n, its loop repeats log[2](n) times, since it takes that many iterations for the doubling of i to reach n.





f is doubly logarithmic - it halves the exponent of n in each operation, for log[2](log[2](n)) repetitions.



We can disregard the fact that g is a separate function - effectively, it is a loop nested within another loop. We can find a better limit if we analyse exactly how the number of repetitions of g decreases as f progresses, but $O(\log n * \log \log n)$ is meh good enough. (Complexity theory is like seafood: while "I ate bluefin tuna" might be the correct answer, "I ate fish" is not wrong.)

EDIT:

However the right answer is O(log(n)) (final test answer) and I don't understand why....

As I said:

We can find a better limit if we analyse exactly how the number of repetitions of g decreases as f progresses

but honestly, this is easier done from results than code. Say n starts off as 65536. This will give us 16 iterations of g. Root of it is 256, which will allow g to run 8 times. Next up is 16, for 4 iterations of g. Then 4 for 2, and 2 for 1. This looks like a geometric progression: 16+8+4+2+1 = 32-1, where $32 = 1 \log[2](65536)$, which is consistent with $O(\log n)$.

Or you could notice that in the first iteration of f there will be a lot of iterations of g, compared to which all the other invocations of g are irrelevant (disappearing logarithmically). Since that first invocation of g is O(log(n)), we can just truncate it there and say that's the complexity.

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edited Aug 29, 2018 at 12:17

answered Aug 29, 2018 at 11:59



Amadan

76k 19 214 272

However the right answer is O(log(n)) (final test answer) and I don't understand why.... - Ron73404 Aug 29, 2018 at 12:01



Big O notation to describe the asymptotic behavior of functions. Basically, it tells you how fast a function grows or declines



For example, when analyzing some algorithm, one might find that the time (or the number of steps) it takes to complete a problem of size n is given by



 $T(n) = 4 n^2 - 2 n + 2$

If we ignore constants (which makes sense because those depend on the particular hardware the program is run on) and slower growing terms, we could say "T(n)" grows at the order of n^2 " and write: $T(n) = O(n^2)$

For the formal definition, suppose f(x) and g(x) are two functions defined on some subset of the real numbers. We write

```
f(x) = O(g(x))
```

(or f(x) = O(g(x))) for x -> infinity to be more precise) if and only if there exist constants N and C such that

```
|f(x)| \leftarrow C|g(x)| for all x>N
```

Intuitively, this means that f does not grow faster than g

If a is some real number, we write

```
f(x) = O(g(x)) for x->a
```

if and only if there exist constants d > 0 and C such that

```
|f(x)| \ll C|g(x)| for all x with |x-a| \ll d
```

So for your case it would be

```
O(n) \text{ as } |f(x)| > C|g(x)|
```

Reference from http://web.mit.edu/16.070/www/lecture/big_o.pdf

```
for r from 0 to xlist: // --> n time
    for c from 0 to ylist: // n time
    sum+= values[r][c]
    n+1
}
```

Big O Notation gives an assumption when value is very big outer loop will run n times and inner loop is running n times

Assume n -> 100 than total n^2 10000 run times

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answered Aug 29, 2018 at 12:36

