

# Chapter 3 Exercise Solutions

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## 3

### 3.1

#### 3.1-1

Let  $f(n)$  and  $g(n)$  be asymptotically nonnegative functions. Using the basic definition of  $\Theta$ -notation, prove that  $\max(f(n), g(n)) = \Theta(f(n) + g(n))$ .

Given constants  $c_1, c_2$  and  $n_0$ , a function  $(m(n) = \max(f(n), g(n))) \in \Theta(f(n) + g(n))$  if and only if  $0 \leq c_1(f(n) + g(n)) \leq m(n) \leq c_2(f(n) + g(n))$ . Since  $m(n) \leq f(n) + g(n)$  we already have an upper bound to work with and can thus default  $c_2$  to just 1.

For the lower bound we can just take the factor  $\min(\frac{f(n)}{f(n)+g(n)}, \frac{g(n)}{f(n)+g(n)})$ , which shrinks the expression  $f(n) + g(n)$  to  $\min(f(n), g(n))$  and therefore is always smaller or equal to  $\max(f(n), g(n))$ .

And thus our function  $m(n)$  satisfies  $0 \leq \min(\frac{f(n)}{f(n)+g(n)}, \frac{g(n)}{f(n)+g(n)})(f(n) + g(n)) \leq m(n) \leq f(n) + g(n), \forall n > 0$  and is indeed in the set of functions described by  $\Theta(f(n) + g(n))$ .

#### 3.1-2

Show that for any real constants  $a$  and  $b$ , where  $b > 0$ ,

$$(n + a)^b = \Theta(n^b).$$

Let us start by showing that  $(n + a)^b = O(n^b)$ . This requires us to find constants  $c, n_0$  such that

$$0 \leq (n + a)^b \leq cn^b, \forall n \geq n_0.$$

Let  $c = 2^b$

$$\Leftrightarrow (n + a)^b \leq (2n)^b$$

and thus we have  $(n + a)^b \leq (2n)^b, \forall n \geq n_0 = |a|$  which implies

$$(n + a)^b = O(n^b).$$

Next we need to show that  $(n+a)^b = \Omega(n^b)$ , which again requires us to find constants  $c, n_0$  such that

$$0 \leq cn^b \leq (n+a)^b, \forall n \geq n_0.$$

Let  $c = (\frac{1}{2})^b$ .

$$\Rightarrow (n+a)^b \geq (\frac{1}{2}n)^b$$

and thus we have  $(n+a)^b \geq (\frac{1}{2}n)^b, \forall n \geq n_0 = 2|a|$  which implies

$$(n+a)^b = \Omega(n^b).$$

And therefore, by Theorem 3.1,  $(n+a)^b = \Theta(n^b)$ .

### 3.1-3

Explain why the statement, “The running time of algorithm A is at least  $O(n^2)$ ”, is meaningless.

Saying that the running time of algorithm A is at least  $O(n^2)$  gives no information about the worst-case running time, because “at least” implies the best-case input. It gives no information on the best-case running time either, since the  $O$ -notation bounds a function from the above, not from below as the  $\Omega$ -notation does. Therefore the statement is to be considered meaningless.

### 3.1-4

Is  $2^{n+1} = O(2^n)$ ?

Inequality to prove:

$$0 \leq 2^{n+1} \leq c \cdot 2^n, \forall n \geq n_0.$$

Let  $c = 2$ , then

$$2^{n+1} \leq 2 \cdot 2^n = 2^{n+1}, \forall n \geq 0.$$

Therefore  $2^{n+1} = O(2^n)$ .

Is  $2^{2n} = O(2^n)$ ?

Inequality to prove:

$$0 \leq 2^{2n} \leq c \cdot 2^n, \forall n \geq n_0.$$

$$2^{2n} \leq c \cdot 2^n$$

$$2^n \leq c$$

There is obviously no constant  $c$  that satisfies

$$\lim_{n \rightarrow \infty} 2^n \leq c,$$

therefore  $2^{2n} \neq O(2^n)$ .

### 3.1-5

Prove Theorem 3.1.

“For any two functions  $f(n)$  and  $g(n)$ , we have  $f(n) = \Theta(g(n))$  if and only if  $f(n) = O(g(n))$  and  $f(n) = \Omega(g(n))$ ” (Theorem 3.1).

Per definition  $\Theta(g(n))$  requires the existence of constants  $c_1, c_2, n_0$  such that

$$0 \leq c_1 \cdot g(n) \leq f(n) \leq c_2 \cdot g(n), \forall n \geq n_0.$$

Therefore we can split of the inequalities as

$$0 \leq c_1 \cdot g(n) \leq f(n), \forall n \geq n_0,$$

which implies  $f(n) = \Omega(n)$ , and

$$0 \leq f(n) \leq c_2 \cdot g(n), \forall n \geq n_0,$$

which implies  $f(n) = O(n)$ .

From the other side of the equivalence, if we have constants  $c_a, c_b, n_a, n_b$  such that

$$0 \leq c_a \cdot g(n) \leq f(n), \forall n \geq n_a,$$

and

$$0 \leq f(n) \leq c_b \cdot g(n), \forall n \geq n_b,$$

we can let  $n_0 = \max(n_a, n_b)$  and thus satisfy

$$0 \leq c_a \cdot g(n) \leq f(n) \leq c_b \cdot g(n), \forall n \geq n_0.$$

### 3.1-6

Prove that the running time of an algorithm is  $\Theta(g(n))$  if and only if its worst-case running time is  $O(g(n))$  and its best-case running time is  $\Omega(g(n))$ .

If the worst-case running time of an algorithm is  $O(g(n))$ , the implication is that the running time is bounded from above (by some function  $f(n) = O(g(n))$ ) for any input of size  $n$ .

Likewise if the best-case running time of an algorithm is  $\Omega(g(n))$ , the implication is that the running time is bounded from below (by some function  $f(n) = \Omega(g(n))$ ) for any input of size  $n$ .

Therefore by Theorem 3.1, that algorithm's running time is  $\Theta(g(n))$ .

Written as an equivalence:

$$\begin{aligned} f(n) \in \Theta(g(n)) & \\ \Leftrightarrow \exists c_1, c_2, n_0 : 0 \leq c_1 g(n) \leq f(n) \leq c_2 g(n), \forall n \geq n_0 & \\ \Leftrightarrow (0 \leq c_1 g(n) \leq f(n) \wedge 0 \leq f(n) \leq c_2 g(n)), \forall n \geq n_0 & \\ \Leftrightarrow f(n) \in \Omega(g(n)) \cap O(g(n)) & \end{aligned}$$

### 3.1-7

Prove that  $o(g(n)) \cap \omega(g(n))$  is the empty set.

For a function  $f(n)$  to be considered a member of  $o(g(n)) \cap \omega(g(n))$ , the following equivalence must be true:

$$\begin{aligned} f(n) \in \omega(g(n)) \cap o(g(n)) & \\ \Leftrightarrow 0 \leq c_1 g(n) < f(n) \wedge 0 \leq f(n) < c_2 g(n) & \\ \Leftrightarrow 0 \leq c_1 g(n) < f(n) < c_2 g(n) & \end{aligned}$$

for all positive real constants  $c_1$  and  $c_2$ , and for all  $n$  bigger than some positive constant  $n_0$ .

But since  $c_1 g(n) < c_2 g(n)$  can't be true for all positive constants  $c_1$  and  $c_2$ ,  $o(g(n)) \cap \omega(g(n))$  must be the empty set.

### 3.1-8

$$O(g(n, m)) = \{f(n, m) : \exists c, n_0, m_0 > 0 : 0 \leq f(n, m) \leq cg(n, m), \forall n \geq n_0 \vee \forall m \geq m_0\}$$

$$\Omega(g(n, m)) = \{f(n, m) : \exists c, n_0, m_0 > 0 : 0 \leq cg(n, m) \leq f(n, m), \forall n \geq n_0 \vee \forall m \geq m_0\}$$

$$\Theta(g(n, m)) = \{f(n, m) : f(n, m) \in \Omega(g(n, m)) \cap O(g(n, m))\}$$

## 3.2

### 3.2-1

Show that if  $f(n)$  and  $g(n)$  are monotonically increasing functions, then so are the functions  $f(n) + g(n)$  and  $f(g(n))$ , and if  $f(n)$  and  $g(n)$  are in addition nonnegative, then  $f(n) \cdot g(n)$  is monotonically increasing.

$f(n)$  and  $g(n)$  being monotonically increasing implies that for  $n \leq m$

$$\begin{aligned} f(n) &\leq f(m) \wedge g(n) \leq g(m) \\ \Leftrightarrow f(n) + g(m) &\geq f(n) + g(n) \\ \Leftrightarrow f(m) + g(m) &\geq f(n) + g(n), \end{aligned}$$

likewise it implies that  $f(g(n)) \leq f(g(m))$ .

If in addition both  $f(n)$  and  $g(n)$  are nonnegative, the following holds

$$\begin{aligned} f(n)g(n) &= f(n)g(n) \\ \Leftrightarrow f(n)g(n) &\leq f(n)g(m) \\ \Leftrightarrow f(n)g(n) &\leq f(m)g(m) \end{aligned}$$

### 3.2-2

Proof equation (3.16).

$$a^{\log_b c} = c^{\log_b a} \tag{3.16}$$

$$\begin{aligned} a^{\log_b c} &= c^{\log_b a} \\ \Leftrightarrow a^{\frac{\log_b c}{\log_b a}} &= c \\ \Leftrightarrow a^{\log_a c} &= c \\ \Leftrightarrow c &= c \end{aligned}$$

### 3.2-3

Prove equation 3.19  $\lg(n!) = \Theta(n \lg n)$ . Also prove that  $n! = \omega(2^n)$  and  $n! = o(n^n)$ .

Let us start with equation **3.19** and by showing its membership to  $O(n \lg n)$ . Let  $c$  be some positive real constant, then

$$\begin{aligned}\lg(n!) &\in O(n \lg n) \\ \Leftrightarrow 0 &\leq \lg(n!) \leq cn \lg n \\ \Leftrightarrow \lg(n^n) &\leq cn \lg n \\ \Leftrightarrow n \lg n &\leq cn \lg n\end{aligned}$$

holds for all  $n \geq n_0 = 1$  if  $c \geq 1$ .

Now we will need to additionally show that  $\lg(n!)$  is also a member of  $\Omega(n \lg n)$ . Again let  $c$  be some positive real constant, then

$$\begin{aligned}\lg(n!) &\in \Omega(n \lg n) \\ \Leftrightarrow 0 &\leq cn \lg n \leq \lg(n!), \forall n > n_0.\end{aligned}$$

By Sterling's approximation we have

$$\begin{aligned}cn \lg n &\leq \lg(n!) \\ \Leftrightarrow cn \lg n &\leq \lg \left( \sqrt{2\pi n} \left( \frac{n}{e} \right)^n \cdot e \right) \\ \Leftrightarrow cn \lg n &\leq \frac{1}{2}(\lg 2\pi + \lg n) + n \lg n - n \lg e + \lg e.\end{aligned}$$

Let  $c = 0.5$ , then we have

$$0 \leq \frac{1}{2}(\lg 2\pi + \lg n) + \frac{n}{2} \lg n - n \lg e + \lg e,$$

which is positive as long as  $\frac{n}{2} \lg n - n \lg e$  is positive.

Therefore

$$\begin{aligned}
& \frac{n}{2} \lg n - n \lg e \geq 0 \\
& \Leftrightarrow \frac{n}{2} (\lg n - 2 \lg e) \geq 0 \\
& \Leftrightarrow \lg n - 2 \lg e \geq 0 \\
& \Leftrightarrow n \geq 2^{2 \lg e},
\end{aligned}$$

and thus there exists  $c = 0.5$  such that

$$0 \leq \frac{1}{2} (\lg 2\pi + \lg n) + \frac{n}{2} \lg n - n \lg e + \lg e,$$

for all  $n \geq n_0 = 2^{2 \lg e}$ , and therefore  $\lg(n!)$  is also element of  $\Omega(n \lg n)$ , which by Theorem 3.1 is equivalent to  $\lg(n!) \in \Theta(n \lg n)$ .

*Prove  $n! = o(n^n)$ .*

We need to show that

$$\lim_{n \rightarrow \infty} \frac{n^n}{n!} = \infty,$$

or alternatively

$$\lim_{n \rightarrow \infty} \frac{n!}{n^n} = 0.$$

We can again make use of Sterling's approximation, such that we have

$$\begin{aligned}
& \frac{n^n}{\sqrt{2\pi n} \left(\frac{n}{e}\right)^n \left(1 + \Theta\left(\frac{1}{n}\right)\right)} \\
&= \frac{e^n}{\sqrt{2\pi n} \left(1 + \Theta\left(\frac{1}{n}\right)\right)} \\
&= \frac{e^n}{\sqrt{2\pi n} \Theta\left(\frac{\sqrt{2\pi n}}{n}\right)} \\
&= \frac{e^n}{\Theta\left(\frac{\sqrt{2\pi n^2}}{n}\right)} \\
&= \frac{e^n}{\Theta(2\pi)} \\
&= \frac{e^n}{\Theta(1)}
\end{aligned}$$

now looking at the limit we have

$$\lim_{n \rightarrow \infty} \frac{e^n}{\Theta(1)} = \infty.$$

Prove  $n! = w(n^n)$ .

We need to show that

$$\lim_{n \rightarrow \infty} \frac{2^n}{n!} = 0,$$

or alternatively

$$\lim_{n \rightarrow \infty} \frac{n!}{2^n} = \infty.$$

Using Sterling's approximation again, we get

$$\begin{aligned} & \frac{2^n}{\sqrt{2\pi n} \left(\frac{n}{e}\right)^n \left(1 + \Theta\left(\frac{1}{n}\right)\right)} \\ &= \frac{(2e)^n}{\sqrt{2\pi n} n^n \left(1 + \Theta\left(\frac{1}{n}\right)\right)} \\ &= \frac{(2e)^n}{\sqrt{2\pi n} (n^n + \Theta(n^{n-1}))} \\ &= \frac{(2e)^n}{\sqrt{2\pi n} \Theta(n^{n-1})} \\ &= \frac{(2e)^n}{\sqrt{2\pi n} \Theta(n^n)} \\ &= \frac{(2e)^n}{\Theta(\sqrt{n}) \Theta(n^n)} \\ &= \frac{(2e)^n}{\Theta(\sqrt{n} n^n)} \\ &= \frac{(2e)^n}{\Theta(n^{n+\frac{1}{2}})} \\ &= \frac{2e}{\Theta(n^{2n^{-1}+1})} \end{aligned}$$

Now looking at the limit, we have

$$\lim_{n \rightarrow \infty} \frac{2e}{\Theta(n^{2n^{-1}+1})} = \frac{2e}{n} = 0.$$

### 3.2-4

Is the function  $\lceil \lg n \rceil!$  polynomially bounded? Is the function  $\lceil \lg \lg n \rceil!$  polynomially bounded?

### 3.2-5

Which is asymptotically larger:  $\lg(\lg * n)$  or  $\lg * (\lg n)$ ?



**3.2-6**

Show that the golden ratio  $\phi$  and its  $\widehat{\phi}$  both satisfy the equation  $x^2 = x + 1$ . We can show this by using the quadratic formula:

$$\begin{aligned} x_{1,2} &= \frac{1}{2} \pm \sqrt{-\frac{1}{2} + 1} \\ &= \frac{1}{2} \pm \sqrt{\frac{5}{4}} \\ &= \frac{1}{2} \pm \frac{\sqrt{5}}{2} \end{aligned}$$

Therefore the first solution to the equation is  $\frac{1-\sqrt{5}}{2} = \widehat{\phi}$  and the second is  $\frac{1+\sqrt{5}}{2} = \phi$ .

**3.2-7**

Prove by induction that the  $i$ th Fibonacci number satisfies the equality

$$F_i = \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}},$$

where  $\phi$  is the golden ratio and  $\widehat{\phi}$  is its conjugate. First we show that it holds for  $i = 1$  and  $i = 2$ .

$$\begin{aligned} F_1 &= \frac{\phi^1 - \widehat{\phi}^1}{\sqrt{5}} \\ &= \frac{\frac{1+\sqrt{5}}{2} - \frac{1-\sqrt{5}}{2}}{\sqrt{5}} \\ &= \frac{1 + \sqrt{5} - (1 - \sqrt{5})}{2\sqrt{5}} \\ &= \frac{2\sqrt{5}}{2\sqrt{5}} = 1 \end{aligned}$$

$$\begin{aligned}
F_2 &= \frac{\phi^2 - \widehat{\phi}^2}{\sqrt{5}} \\
&= \frac{\left(\frac{1+\sqrt{5}}{2}\right)^2 - \left(\frac{1-\sqrt{5}}{2}\right)^2}{\sqrt{5}} \\
&= \frac{(1+\sqrt{5})^2 - (1-\sqrt{5})^2}{4\sqrt{5}} \\
&= \frac{1+2\sqrt{5}+5 - (1-2\sqrt{5}+5)}{4\sqrt{5}} \\
&= \frac{4\sqrt{5}}{4\sqrt{5}} = 1
\end{aligned}$$

Now assuming that the equality holds for  $F_{i-2}$  and  $F_{i-1}$ , we will show that it also holds for  $F_i$  by showing that  $F_i = F_{i-2} + F_{i-1}$  as this is the property of the Fibonacci sequence.

$$\begin{aligned}
F_i &= F_{i-2} + F_{i-1} \\
\Leftrightarrow \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}} &= \frac{\phi^{i-2} - \widehat{\phi}^{i-2}}{\sqrt{5}} + \frac{\phi^{i-1} - \widehat{\phi}^{i-1}}{\sqrt{5}} \\
\Leftrightarrow \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}} &= \frac{\phi^{i-2} - \widehat{\phi}^{i-2} + \phi^{i-1} - \widehat{\phi}^{i-1}}{\sqrt{5}} \\
\Leftrightarrow \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}} &= \frac{\phi^{i-1} + \phi^{i-2} - \widehat{\phi}^{i-1} - \widehat{\phi}^{i-2}}{\sqrt{5}} \\
\Leftrightarrow \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}} &= \frac{\phi^{i-2}(\phi^1 + 1) - \widehat{\phi}^{i-2}(\widehat{\phi}^1 + 1)}{\sqrt{5}} \\
\Leftrightarrow \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}} &= \frac{\phi^{i-2}(\phi^2) - \widehat{\phi}^{i-2}(\widehat{\phi}^2)}{\sqrt{5}} \\
\Leftrightarrow \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}} &= \frac{\phi^i - \widehat{\phi}^i}{\sqrt{5}}
\end{aligned}$$