

# Data Structures in Python

## Chapter 2

1. Abstract Data Type(ADT)
2. Performance Analysis
3. Big-O Notation
- 4. Growth Rate**
5. Growth Rate Examples

# Agenda & Reading

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- Performance Analysis
  - Introduction
  - Step Counts - Counting Operations
- Big-O Notation - Asymptotic Analysis
  - Properties of Big-O
  - Calculating Big-O
- **Growth Rate**
  - **Comparison**
  - **Profiling and Prediction**
- Growth Rate Examples
  - Python List & Dictionary
- References:
  - Textbook: Problem Solving with Algorithms and Data Structures
    - Chapter 3. [Analysis](#)
  - Textbook: [www.github.idebtor/DSPy](http://www.github.idebtor/DSPy)
    - Chapter 2.1 ~ 3

# 1 Growth Rate Comparison - Hypothetical Running Time

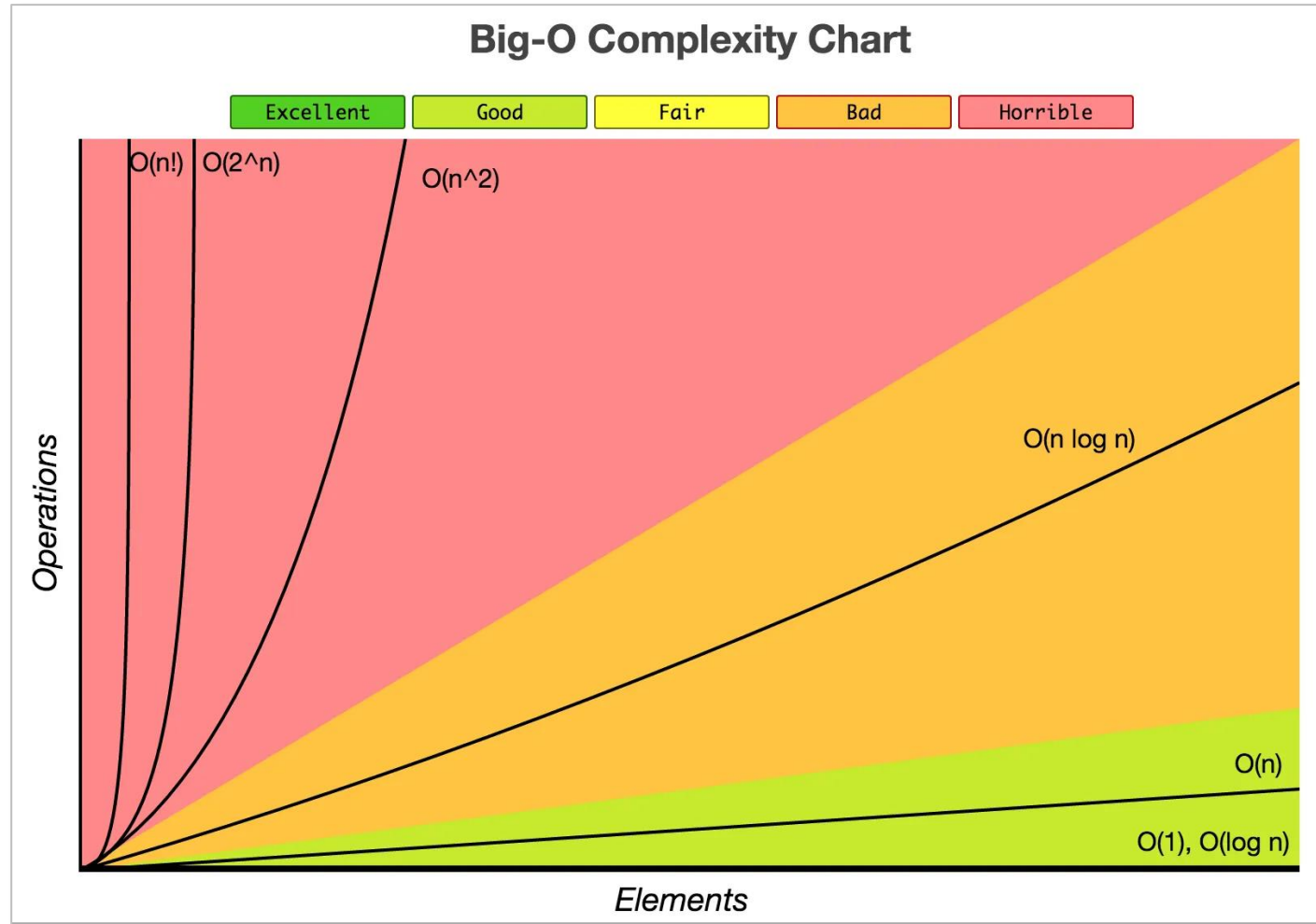
- The running time on a hypothetical computer that computes  $10^6$  operations per second for various problem sizes

$$O(1) < O(\log n) < O(n) < O(n \log n) < O(n^2) < O(n^3) < O(2^n)$$

Notation			$n = 10$	$n = 10^2$	$n = 10^3$	$n = 10^4$	$n = 10^5$	$n = 10^6$
$O(1)$	Constant	상수	1 $\mu$ sec	1 $\mu$ sec	1 $\mu$ sec	1 $\mu$ sec	1 $\mu$ sec	1 $\mu$ sec
$O(\log(n))$	Logarithmic	대수 함수	3 $\mu$ sec	7 $\mu$ sec	10 $\mu$ sec	13 $\mu$ sec	17 $\mu$ sec	20 $\mu$ sec
$O(n)$	Linear	선형 함수	10 $\mu$ sec	100 $\mu$ sec	1 msec	10 msec	100 msec	1 sec
$O(n \log(n))$	$N \log N$	선형 대수 함수	33 $\mu$ sec	664 $\mu$ sec	10 msec	13.3 msec	1.6 sec	20 sec
$O(n^2)$	Quadratic	2차 함수	100 $\mu$ sec	10 msec	1 sec	1.7 min	16.7 min	11.6 days
$O(n^3)$	Cubic	3차 함수	1 msec	1 sec	16.7 min	11.6 days	31.7 years	31709 years
$O(2^n)$	Exponential	지수 함수	10 msec	3e17 years				

# 1 Growth Rate Comparison

$$O(1) < O(\log n) < O(n) < O(n \log n) < O(n^2) < O(n^3) < O(2^n)$$

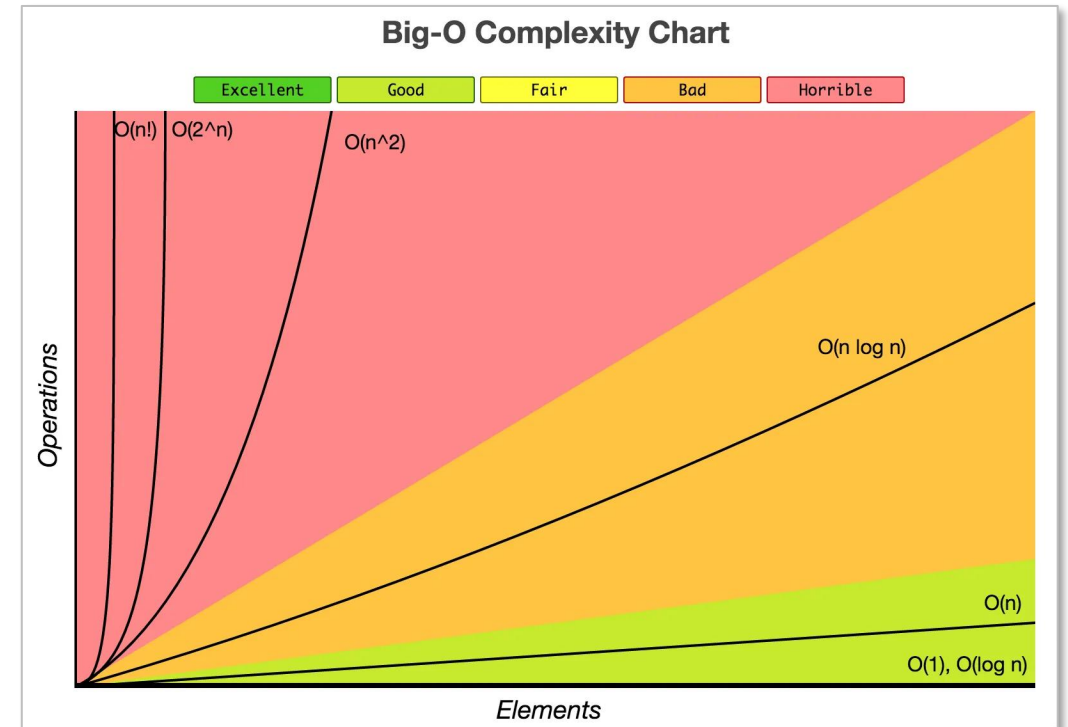
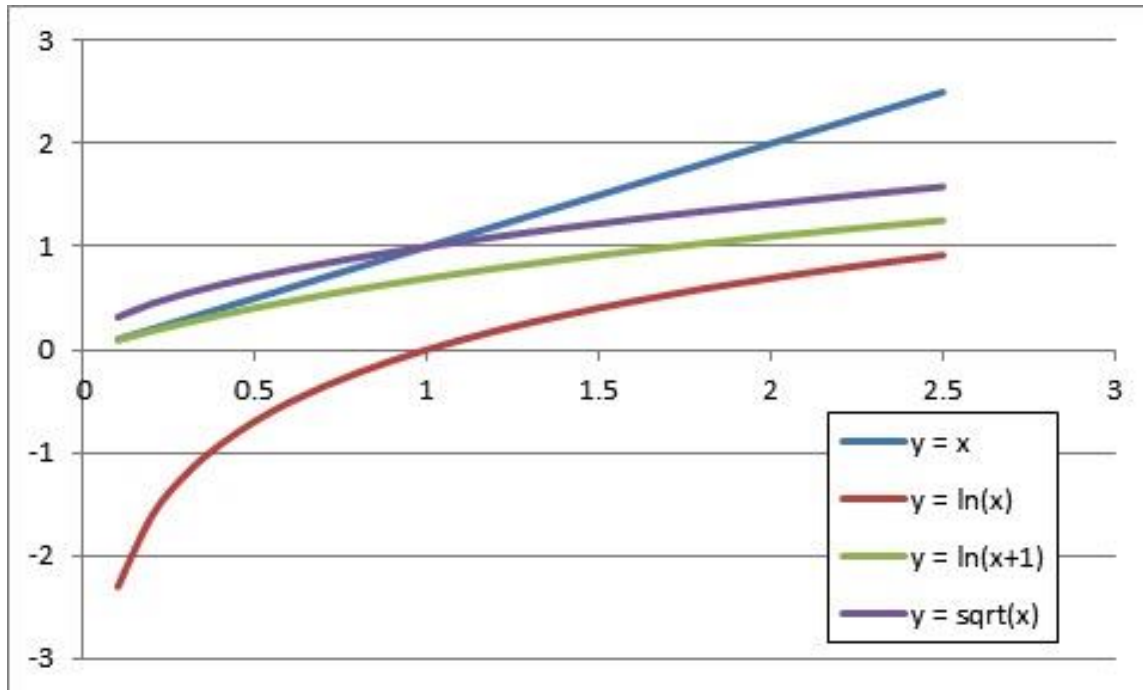


A comparison of growth-rate functions in graphical form

# 1 Growth Rate Comparison

$$O(1) < O(\log n) < O(n) < O(n \log n) < O(n^2) < O(n^3) < O(2^n)$$

$$T(N) \approx aN^b$$

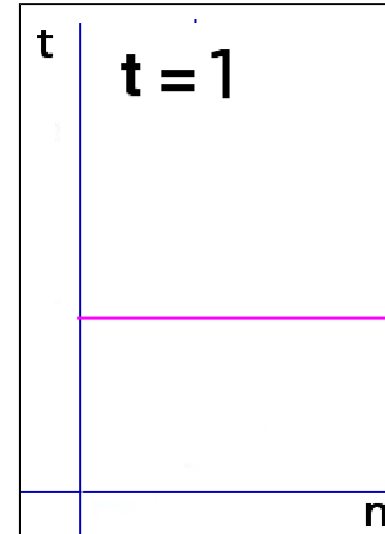


A comparison of growth-rate functions in graphical form

## 2 Growth Rate Examples - Constant Growth Rate - $O(1)$

- Time requirement is constant and, therefore, **independent of the problem's size  $n$** .

```
def rate1(n):  
    s = "SWEAR"  
    for i in range(25):  
        print("I must not ", s)
```

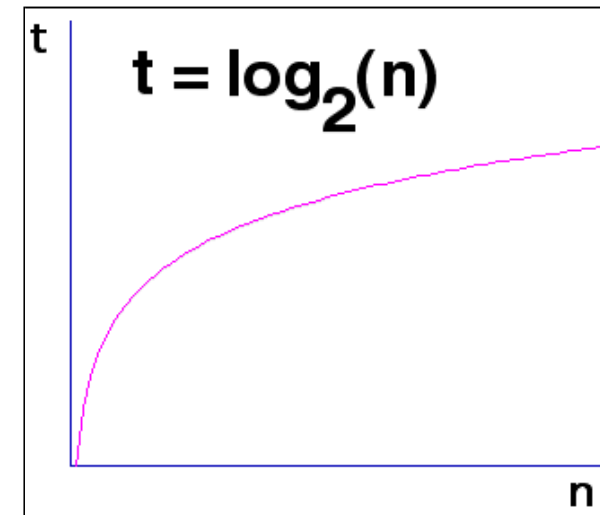


n	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(1)$	1	1	1	1	1	1

## 2 Growth Rate Examples - Logarithmic Growth Rate - $O(\log n)$

- Increase **slowly** as the problem size increases.
- If you square the problem size, you only double its time requirement.
- The base of the log does not affect a log growth rate, so you can omit it.

```
def rate2(n):  
    s = "YELL"  
    i = 1  
    while i < n:  
        print("I must not ", s)  
        i = i * 2
```

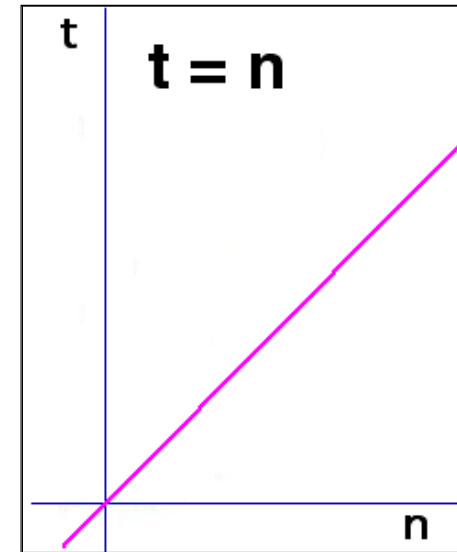


$n$	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(\log_2 n)$	3	6	9	13	16	19

## 2 Growth Rate Examples - Linear Growth Rate - $O(n)$

- The time increases directly with the sizes of the problem.
- If you square the problem size, you also square its time requirement.

```
def rate3(n):  
    s = "FIGHT"  
    for i in range(n):  
        print("I must not ", s)
```



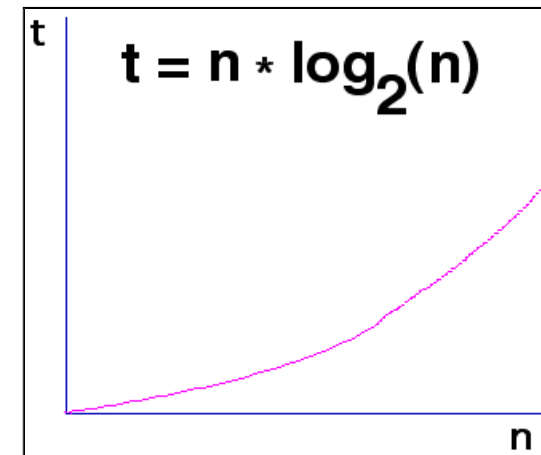
n	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(n)$	10	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$



## 2 Growth Rate Examples - $n * \log n$ Growth Rate - $O(n \log(n))$

- The time requirement increases more rapidly than a linear algorithm.
- Such algorithms usually divide a problem into smaller problem that are each solved separately.

```
def rate4(n):  
    s = "HIT"  
    for i in range(n):  
        j = n  
        while j > 1:  
            print("I must not ", s)  
            j = j // 2
```

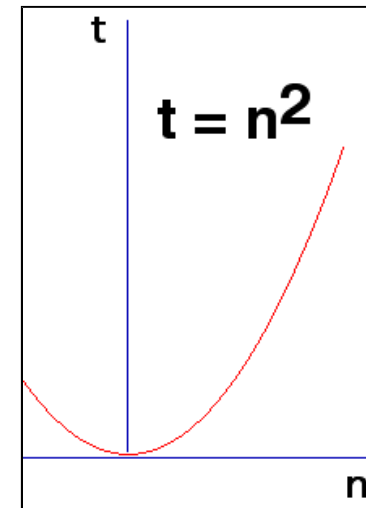


n	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(n \log(n))$	30	664	9965	$10^5$	$10^6$	$10^7$

## 2 Growth Rate Examples - Quadratic Growth Rate - $O(n^2)$

- The time requirement increases rapidly with the size of the problem.
- Algorithms that use two nested loops are often quadratic.

```
def rate5(n):  
    s = "LIE"  
    for i in range(n):  
        for j in range(n):  
            print("I must not ", s)
```



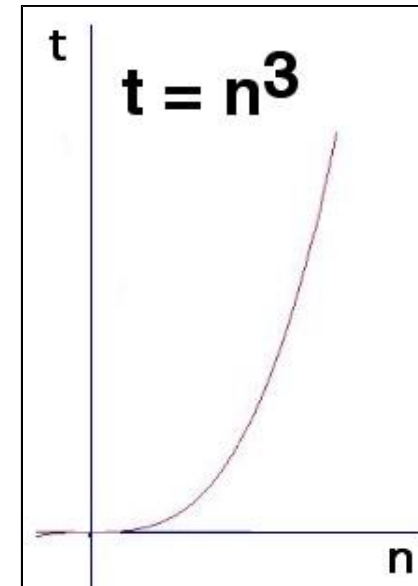
$n$	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(n^2)$	$10^2$	$10^4$	$10^6$	$10^8$	$10^{10}$	$10^{12}$

## 2 Growth Rate Examples - Cubic Growth Rate - $O(n^3)$

- The time requirement increases more rapidly with the size of the problem than the time requirement for a quadratic algorithm.
- Algorithms that use three nested loops are often quadratic and are practical only for small problems.

```
def rate6(n):  
    s = "SPACE OUT IN CLASS"  
    for i in range(n):  
        for j in range(n):  
            for k in range(n):  
                print("I must not ", s)
```

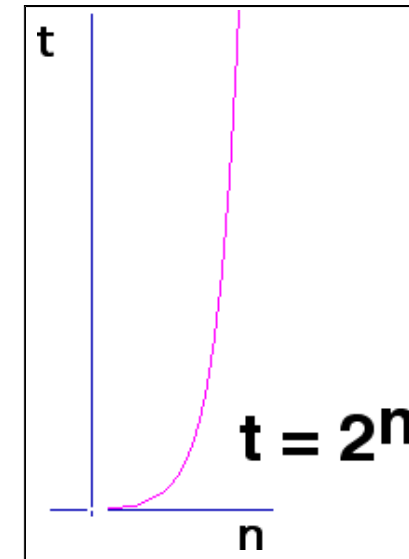
n	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(n^3)$	$10^3$	$10^6$	$10^9$	$10^{12}$	$10^{15}$	$10^{18}$



## 2 Growth Rate Examples - Exponential Growth Rate - $O(2^n)$

- As the size of a problem increases, the time requirement usually increases too rapidly to be practical.

```
def rate7(n):  
    s = "ZONE OUT IN CLASS"  
    for i in range(2 ** n):  
        print("I must not ", s)
```



$n$	$10^1$	$10^2$	$10^3$	$10^4$	$10^5$	$10^6$
$O(2^n)$	$10^3$	$10^{30}$	$10^{301}$	$10^{3010}$	$10^{30103}$	$10^{301030}$

## Exercise

- What is the Big-O of the following statements?

<pre>for i in range(n):     for j in range(10):         print(i, j)</pre>	<pre>executed n times executed 10 times constant time</pre>
-----------------------------------------------------------------------------------	---------------------------------------------------------------------

- Running time,  $T(n) = n * 10 * 1 = 10n$ , Big-O =
- What is the Big-O of the following statements? Big-O =

<pre>for i in range(n):     for j in range(n):         print(i, j)</pre>	<pre>executed n times executed n times</pre>
<pre>for k in range(n):     print(k)</pre>	<pre>executed n times</pre>

- The first set of nested loops is  $O(n^2)$  and the second loop is  $O(n)$ .  
This is  $O(\max(n^2, n))$  Big-O =

## Exercise

- What is the Big-O of the following statements?

<pre>for i in range(n):     for j in range(10):         print(i, j)</pre>	<pre>executed n times executed 10 times constant time</pre>
-----------------------------------------------------------------------------------	---------------------------------------------------------------------

- Running time,  $T(n) = n * 10 * 1 = 10n$ , Big-O =  $O(n)$

- What is the Big-O of the following statements? Big-O =

<pre>for i in range(n):     for j in range(n):         print(i, j)</pre>	<pre>executed n times executed n times</pre>
<pre>for k in range(n):     print(k)</pre>	<pre>executed n times</pre>

- The first set of nested loops is  $O(n^2)$  and the second loop is  $O(n)$ .  
This is  $O(\max(n^2, n))$  Big-O =  $O(n^2)$

# Quiz

- What is the Big-O of the following statements?

```
for i in range(n):  
    for j in range(i+1, n):  
        print(i, j)
```

- When  $i$  is 0, the inner loop executes  $(n - 1)$  times.  
When  $i$  is 1, the inner loop executes  $(n - 2)$  times.  
...  
When  $i$  is  $(n - 2)$ , the inner loop executes once.
- The number of times the inner loop statements execute:
  - Running time,  $T(n) =$
  - Big-O =

### 3 Profiling: Measuring Growth Rate

**Problem:** Predict the running time of a big data set (i.e.,  $n = 1$  million or 1 billion).

- Most algorithms approximately have the order of growth of the running time:

$$T(N) \approx aN^b$$

- For example, we may compute the constant "a" and the growth rate "b" from data we got from profiling (i.e., performance analysis) as shown below.

N	sec
1000	0.000949
2000	0.001706
3000	0.002773
4000	0.004145
5000	0.004781
6000	0.005814
7000	0.006897
8000	0.008350
9000	0.009346
10000	0.009941



### 3 Profiling: Measuring Growth Rate

**Problem:** Predict the running time of a big data set (i.e.,  $n = 1$  million or 1 billion).

- Most algorithms approximately have the order of growth of the running time:

$$T(N) \approx aN^b$$

- For example, we may compute the constant "a" and the growth rate "b" from data we got from profiling (i.e., performance analysis) as shown below.
- Since  $T(N) \approx a N^b$ ,  $T(2N) = a (2N)^b$ , then

$$\frac{T(2N)}{T(N)} = \frac{a(2N)^b}{aN^b} = \frac{2^b(N)^b}{N^b} = 2^b$$

Take log both sides

$$\log \frac{T(2N)}{T(N)} = \log 2^b$$

$$b = \log \frac{T(2N)}{T(N)}$$

### 3 Profiling: Measuring Growth Rate - Example

- **Example:** let us choose  $N = 4000$  or  $2N = 8000$ , an average case of the insertion sort shown above. Recall that log we use here is **log base 2**.

$$b = \log \frac{T(2N)}{T(N)} = \log \frac{t_2(8000)}{t_1(4000)} = \log \frac{0.036643}{0.011144} = 1.717$$

- Now, we use this  $b = 1.717$  to solve for  $a$  when  $N = 4000$ ,  $T(N) = 0.011144$  in the following:

$$\begin{aligned} T(N) &= a N^{1.717} \\ 0.011144 &= a (4000)^{1.717} \\ a &= \frac{0.011144}{(4000)^{1.717}} \\ a &= 7.27 \times 10^{-9} \end{aligned}$$

- Therefore, we have the growth rate  $b = 1.717$ , **the constant**  $a = 7.27 \times 10^{-9}$  for the insertion sort average case.

# Summary

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- Performance analysis or profiling measures an algorithm's time requirement as a function of the problem size **n** by **using a growth-rate** function.
- The **growth rates** shown below are commonly used :

$$O(1) < O(\log n) < O(n) < O(n \log n) < O(n^2) < O(n^3) < O(2^n)$$

- Generally, **growth rates** can be measured in a form of the following:

$$T(N) \approx aN^b$$