

Time and Space Complexity.

What is time and space complexity?

- Time and Space Complexity are two fundamentals concepts for us to analyse the efficiency of an algorithm.

efficiency is how much ~~space and time~~
a program took to run a specific
task.

what is Time Complexity

Time complexity tells us the growth (O) in runtime of algorithm as the input increases.

In simple words.

Simple words.
→ The time required by the algorithm to solve given problem is called time complexity of the algorithm.

It tells us how the number of operation increases as the size of input increases.

→ we measure Time Complexity by counting its operations in a program.

It is measured in Big-O Notation.

more simple definition

→ Time Complexity is a way to tell us how the time to run an algorithm increase with the size of the input data.

The Three Notations.

Notations are used to describe how an algorithm performs as the input increases.

there are three types of notation.

- ① Big O (O) → worst case performance.
- ② Big Theta (Θ) → Average or typical performance.
- ③ Big Omega (Ω) → Best-case performance.

① Big O Notation (O)

→ It tells us the maximum time effort it may use our code might use.

This is also called as the worst case scenario. and we typically takes it use this.

$$O(1), O(N), O(N^2)$$

→ upper Bound.

②. Big Theta Notation (Θ)

- It shows the typical time or memory used
— not too fast or not too slow.
- It tells us the average how the algorithm performs on average. (average)

Big Omega Notation (Ω)

- It tells us the minimum time or memory required in the worst case.
- It shows the lower bound for the algorithm in your code which will always be true.

Now, an Depth of Big O (O) Notation

①

$O(1)$

→ constant
The execution time is constant regardless of input size.

②

int a = arr[5];

Example:

$O(1)$

③

$O(n)$

→ linear.
The time grows directly with input size.

for (int i = 1; i < n; i++) {
System.out.println(i); }

(3) visit all elements once for each item.

* The loop runs once for each item.
↳ You visit every element once.

↳ You visit every element once.

→ It is very common in loops over arrays or lists.

↳ logarithmic

⑧ $O(n)$ — linear time.

→ When an algorithm cuts the input size in half (or reduces it significantly) with each step, it remains logarithmic time.

→ The time grows very slowly even as input gets large.

→ It is like divide and conquer.

→ It is

→ Common in binary search trees.

④ $O(n \log n)$ — linearithmic time

→ It is a combination of linear and logarithmic — It is faster than $O(n^2)$, but slower than $O(n)$.

→ It is like doing a linear loop, but inside each step, you're also doing a $O(n)$ operation (like dividing).

- but for comparison-based sorting.
- shows up in merge sort, quick sort, heap sort.

```

int[] arr = {5, 3, 8, 2, 1, 4};
Array.sort(arr);
for (int num : arr) {
    System.out.println(num + " ");
}

```

- ⑤ $O(n^2)$ - Quadratic Time
- An algorithm is said to have $O(n^2)$ time complexity when the running time increases proportionally to the square of the input size.

- As the input grows, time grows faster -
 $\rightarrow (n+1)^2 \text{ diff. time} > n^2 \text{ diff. time}$
- It is very common in nested loop.
- Mostly used in Bubble sort, Selection sort, (Comparing each element pair of elements) + n^2 time.
- Brute force solution.

① $O(2^n)$ - Exponential Time: time doubles with each added input

↳ Time doubles with each added input.

↳ If $n=2, 3$, inputs increase by 1.
each time the inputs increase by 1.
operations double. grows exponentially fast.
(" " + more) taking two strategies
merely used " "

↳ Recursion

↳ Subset generation

and $(^n)_0$ solving the Fibonacci number naively.
answer will be $\text{Backtracking algorithm}$.
begin with intervals up to m .
begin with m steps of $2 \times 2 \times 2 \times \dots \times 2$ (in nine)
do for input size m , $= 2^9$ permutations

- return
public static int fib(int n) {
 if (n <= 1) return n;
 return fib(n-1) + fib(n-2);
}

public PSUM (String args) {
 int n = 10;
 int sum = 0;
 for (int i = 0; i < n; i++)
 sum += fib(i);
 System.out.println("Sum of first " + n + " terms is " + sum);
}

It is very slow if the input size is large.

$O(n!)$ - Factorial Time.

→ An algorithm has $O(n!)$ time complexity when the number of operations grows factorially with the size of input n .

→ If you increase the input size even a little, the time explodes!

$$n! = n \times (n-1) \times (n-2) \times \dots \times 1$$

→ usually used in Permutations and Combinations where all possibilities must be explored.

→ It tries every possible permutation for n elements. For $n=5$, you try $5!$ combinations.

Workload Short

one loop = $O(n)$

nested loop = $O(n^2)$

Cut in half each time $O(n \log n)$

divide and conquer with merge: $O(n \log n)$

Recursion doubling $\rightarrow O(2^n)$

every combo, permutation & combination $\rightarrow O(n!)$

Calculating Big-O Time Complexity (n)

with nested operations and loops (like) and arithmetic op's
with other operations except for parts of algorithm

- ① Break the code into parts

- loops
- function calls
- conditionals
- Basic operations (like $+,-,=,\text{print}$)

• Characteristics how will return
• Complexity Rules to Calculate in few cases e.g. dividing the code

- ① If Single Loop → Add $O(N)$
- ② If Nested Loop → Add $O(n^2)$

- ③ Deeps constants

→ means remove all the constant value while calculating the time complexity.

EXAMPLE

PSV `Print(int n) {` with base case is $O(1)$

$O(n)$ for ($i = 0; i < n; i++$) { $O(n)$ base case is $O(1)$

S.out.println(i); $O(n)$ + $O(n)$ = $O(n^2)$ overall complexity

$O(n)$ for ($j = 0; j < n; j++$) { $O(n)$ base case is $O(1)$

S.out.println(j); } $O(n)$

So, we will have, $n + n = 2n$ (2)
 $\Rightarrow O(2n)$

Now, According to the rule we have to drop the constant term, also note that $O(n^2)$ is more than $O(n)$. So, we have to drop $O(n)$.

④ Dropping Non-Dominant Term

→ Remove all the non-Dominant terms while calculating the time complexity.

EXAMPLE

Example code

```
public static void printn (int n) {
```

```
    for (int i = 0; i < n; i++) { }  $\rightarrow O(n)$ 
```

$O(n^2)$ $\rightarrow O(n^2)$

```
    for (int j = 0; j < n; j++) { }  $\rightarrow O(n)$ 
```

↓ $\rightarrow O(n^2)$

```
    for (int k = 0; k < n; k++) { }  $\rightarrow O(n)$ 
```

$O(n^2) + O(n)$

↓

}

So, we have $O(n^2) + O(n)$

So, according to the rule we have to drop the non-dominant term. So drop $O(n)$.

→ Final $\Rightarrow O(n^2)$

(5) Add and Multiply

$n_0 = n + m$, and this is ok

$(n_0)^0$

Spends on ① Adding the Sequential code blocks
 → when the code blocks are ~~not inside~~ ^{two types} each other
 Sequential m not inside the code block itself, but outside it.

Example -

General unit - $\{ \text{for } (\text{int } i=0; i < n; i++) \{ \text{s.out.print}(i); \}$

$O(n)$ { above element }

$3(n \text{ twi}) \text{ for } (\text{int } i=0; i < n; i++) \{ \text{s.out.print}(i); \}$

$(n)O(n) = 3(n \text{ twi}) \text{ for } (\text{int } i=0; i < n; i++) \{ \text{s.out.print}(i); \}$

EXAMPLE

Since both of them are different and there are Sequential, so the rule is to add it.

$[nO(n) + O(n)]$

$\Rightarrow (n + 1) \text{ twi}$ ref

$(n)^0 + (n)^0$ and we get

with parts of each other where with a different

② Multiplications of two powers (marked ①)

→ when the code is inside each other,
means operations are nested. Hence
we have to do multiply for both.

→ $O(n) \times O(m)$ will be written as:

EXAMPLE

→ $\text{for}(\text{int } i=0; i < n; i++) \{ \rightarrow O(n)$
 $\quad \quad \quad \text{s.out.println}(i); \}$

$n \times m$ times $\text{for}(\text{int } j=0; j < n; j++) \{ \rightarrow O(n)$
 $\rightarrow O(n^2)$ $\quad \quad \quad \text{s.out.println}(j); \}$

(as) $O = n$ \rightarrow Hope we need \leftarrow

∴ as it is nested, we have to multiply it.

$$n \times n = n^2$$

∴ the final time = $O(n^2)$

Space Complexity

→ Space complexity is the total amount of memory
algorithm or program needs based on the size
of the input.

If includes:

- memory for input
- Memory for variable
- Memory for function call
- Memory for data structure like
arrays, list, hash map etc.

- ① Count memory used by variable.
- `int`, `bool`, `string`, variable $\rightarrow O(1)$ space
 - Array of size n $\rightarrow O(n)$ space.
 - 2D matrix of size $n \times n \rightarrow O(n^2)$ space

② Count Entering i used in function
cells (like recursion)

(n) \leftarrow Each recursive call uses stack
space

\hookrightarrow Recursive depth of $n = O(n)$

area $O(n)$ = sum area of all subproblems

problem to be solved will be in phases and
will be handled recursively so multiple

Basis Concepts to Remember.

Integer. Max-value → If it is the highest integer for max value of any integer then

Integer. Min-value → It is the lowest integer among all values of any integer.

when to use for or while loop?

→ ~~for~~ ~~while~~ loop is used, when we don't know whether we have to increment the counter in [first or anywhere in the code].

But when we know that the increment can be done in the starting of the next execution.

[2]

[1]

[5-8]

[1-2, 5]

[2, 5-8]

[1-2, 3-5]

→ lowest . Weip those we are most
rely in them. Then we