

Recap

- Linked List
 - Single
 - Double
 - Circular
- Data and Address/Pointer of Next node/element
- data of 5th/ 5 and None
- Head & Tail

Single Linked List

In [20]: ▶

```
1 class Node:
2     def __init__(self, data):
3         self.data = data
4         self.next_node = None
5
6 class LinkedList:
7     def __init__(self):
8         self.head = None
9         self.num_of_nodes = 0
10    def append_start(self, data):
11
12        self.num_of_nodes += 1
13
14        # pointer of every node
15        new_node = Node(data)
16
17        # no elements in linked list
18        if not self.head:
19            self.head = new_node
20
21        # add 1 ele with none and self.head 1st ele address
22        # add 2 ele add 1 ele address 2nd ele then 2 nd none and data of
23        # atleast 1 item in linked list
24        else:
25            new_node.next_node = self.head
26            self.head = new_node
27
28    def size(self):
29        return self.num_of_nodes
30
31    def traverse(self):
32        present_node = self.head
33        while present_node is not None:
34            print(present_node.data)
35            present_node = present_node.next_node
36
37    def append_end(self, data):
38        self.num_of_nodes += 1
39        new_node = Node(data)
40        present_node = self.head
41        # 1 2 3 ....6
42        while present_node.next_node is not None:
43            present_node = present_node.next_node
44        present_node.next_node = new_node
```

In [26]: ▶

```
1 ll = LinkedList()
```

```
In [13]: 1 ll.append_start(1)
        2 ll.append_start(2)
        3 ll.append_start(3)
        4 ll.append_start(4)
        5 ll.append_start(5)
        6 ll.append_start(6)
        7
        8 ll.size()
```

Out[13]: 6

```
In [14]: 1 ll.traverse()

        6
        5
        4
        3
        2
        1
```

```
In [ ]: 1 [6 addr5 4 addr3 3 addr2 2 addr1 1 None]
```

```
In [ ]: 1 li = [4 add6, 6 add5, 5 none]
```

```
In [ ]: 1 self.head = addr1
        2
        3 [1 addr3, 3 addr4, 4 addr5, 5 add6, 6 None]
        4
        5 next add to previous ele
        6 break
        7 2
        8 2 addr3
        9
       10 1
       11 2
       12 3
       13 4
       14 5
       15 6
       16 stop
```

In []: ▶

```
1 self.head = addr1
2 7 addr7
3 [1 addr3, 3 addr4, 4 addr5, 5 add6, 6 None]
4
5 1
6 2
7 3
8 4
9 5
10 6
11
12 addr7 to 6th element
13 7th element none
14
15 [1 addr2, 2 addr3, 3 addr4, 4 addr5, 5 add6, 6 addr7, 7]
16
```

```
In [27]: 1 ll.append_start(1)
          2 ll.append_start(2)
          3 ll.append_start(3)
          4 ll.append_start(4)
          5 ll.append_start(5)
          6 ll.append_start(6)
          7
          8 print(ll.size())
          9 ll.traverse()
         10 print('-----')
         11 ll.append_end(1)
         12 ll.append_end(2)
         13 ll.append_end(3)
         14 ll.append_end(4)
         15 ll.append_end(5)
         16 ll.append_end(6)
         17
         18 print(ll.size())
         19 ll.traverse()
```

```
6
6
5
4
3
2
1
-----
12
6
5
4
3
2
1
1
2
3
4
5
6
```

Time Complexity

```
1 A person Application 5min
2 B person Application 3min
3 C person Application <0.5 min
4
5 A & B try to application <0.1 min
```

- Big O Notation -> 5 sec Worst Case Scenario/ rare scenario -> less than worsty case runtime
- Omega Notation -> 1 sec Best Case scenario/ > 1 sec
- Theta Notation -> average-case complexity -> Between 1 and 5

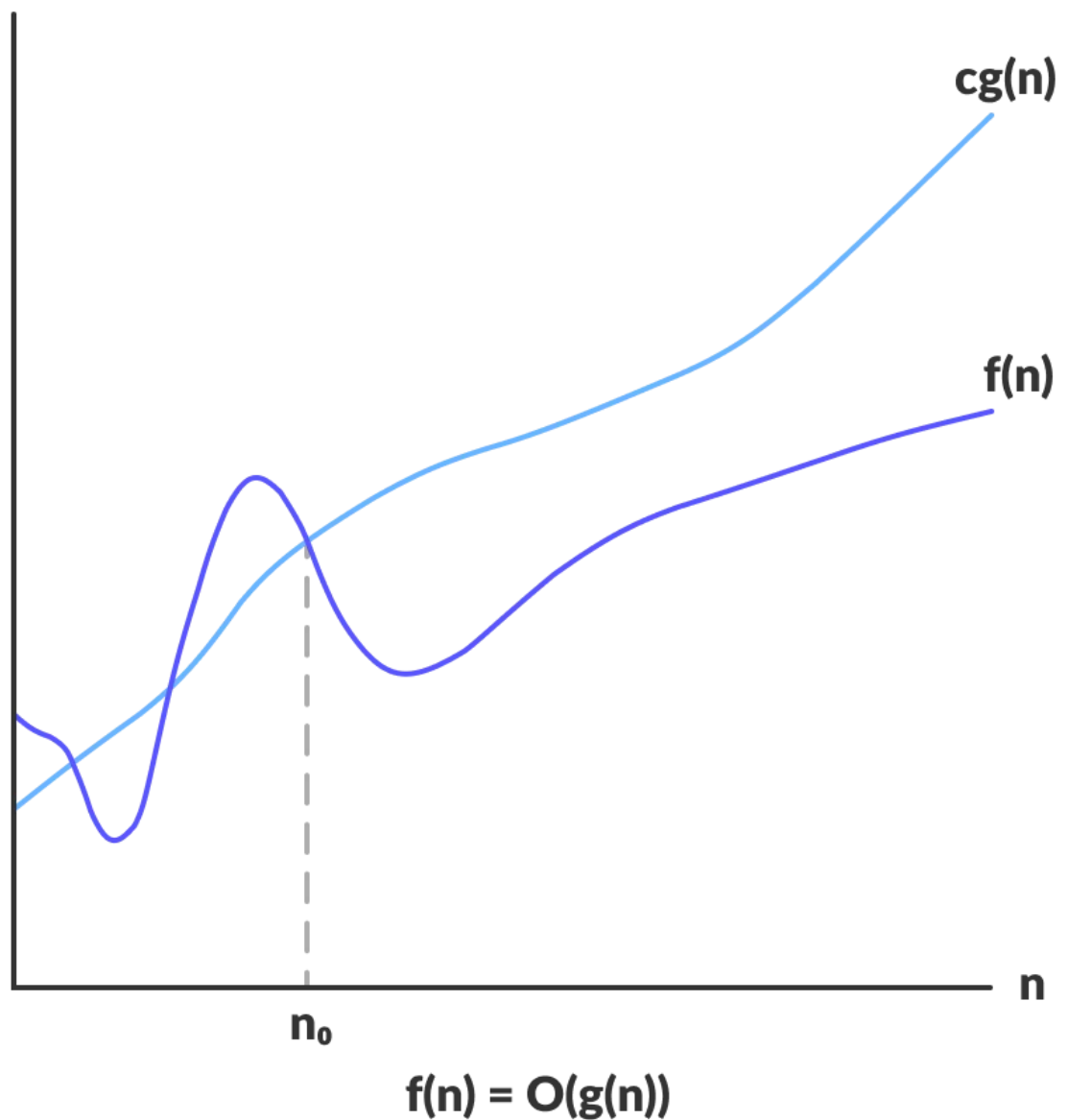
$$c_1 \cdot g(n) < f(n)$$

$$c_2 \cdot g(n) > f(n)$$

$$c_1 g(n) < f(n) < c_2 g(n)$$

Big-O Notation (O-notation)

Big-O notation represents the upper bound of the running time of an algorithm. Thus, it gives the worst-case complexity of an algorithm.



Big-O gives the upper bound of a function

$$O(g(n)) = \{ f(n): \text{there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \leq f(n) \leq cg(n) \text{ for all } n \geq n_0 \}$$

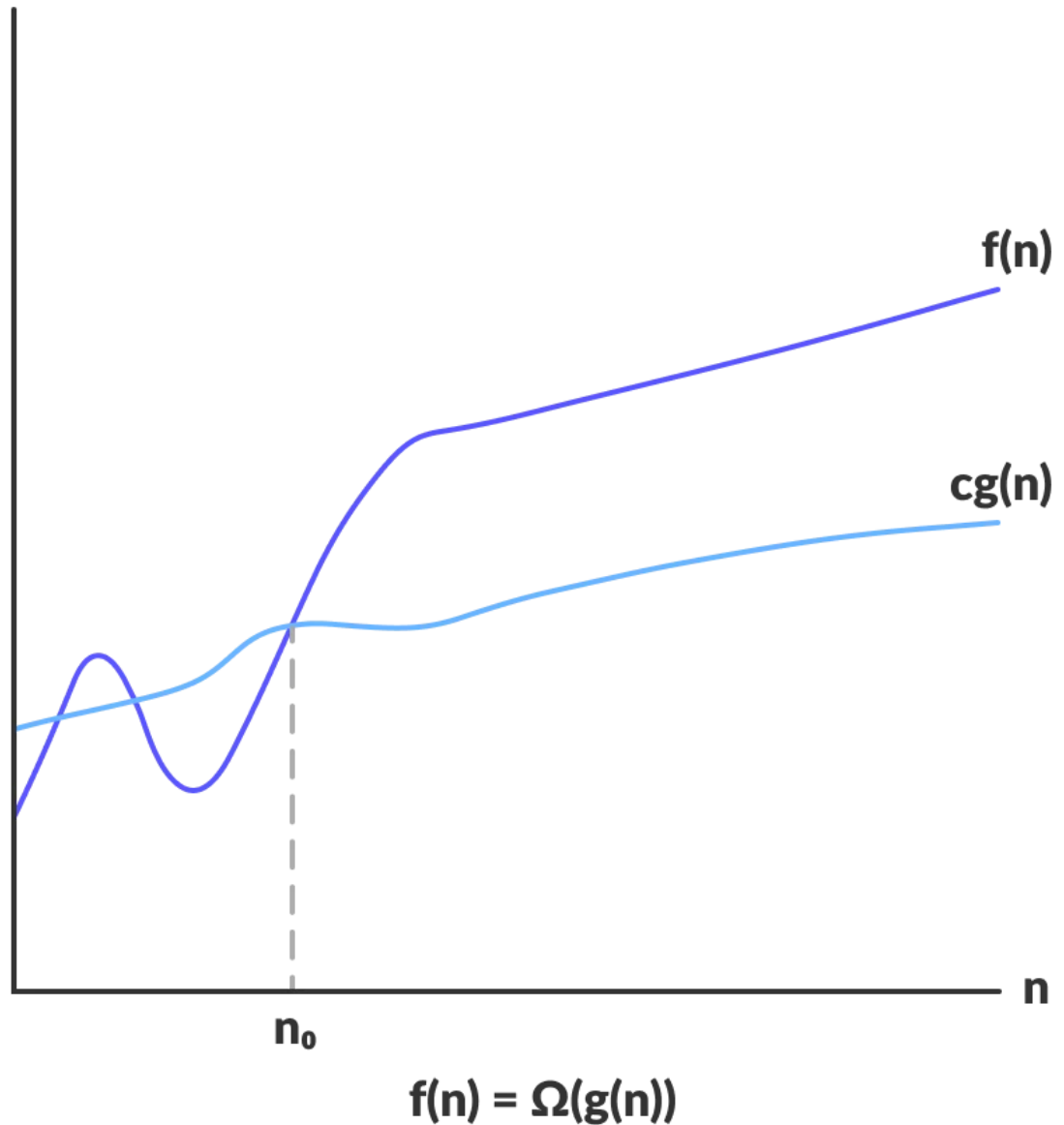
The above expression can be described as a function $f(n)$ belongs to the set $O(g(n))$ if there exists a positive constant c such that it lies between 0 and $cg(n)$, for sufficiently large n .

For any value of n , the running time of an algorithm does not cross the time provided by $O(g(n))$.

Since it gives the worst-case running time of an algorithm, it is widely used to analyze an algorithm as we are always interested in the worst-case scenario.

Omega Notation (Ω -notation)

Omega notation represents the lower bound of the running time of an algorithm. Thus, it provides the best case complexity of an algorithm.



Omega gives the lower bound of a function

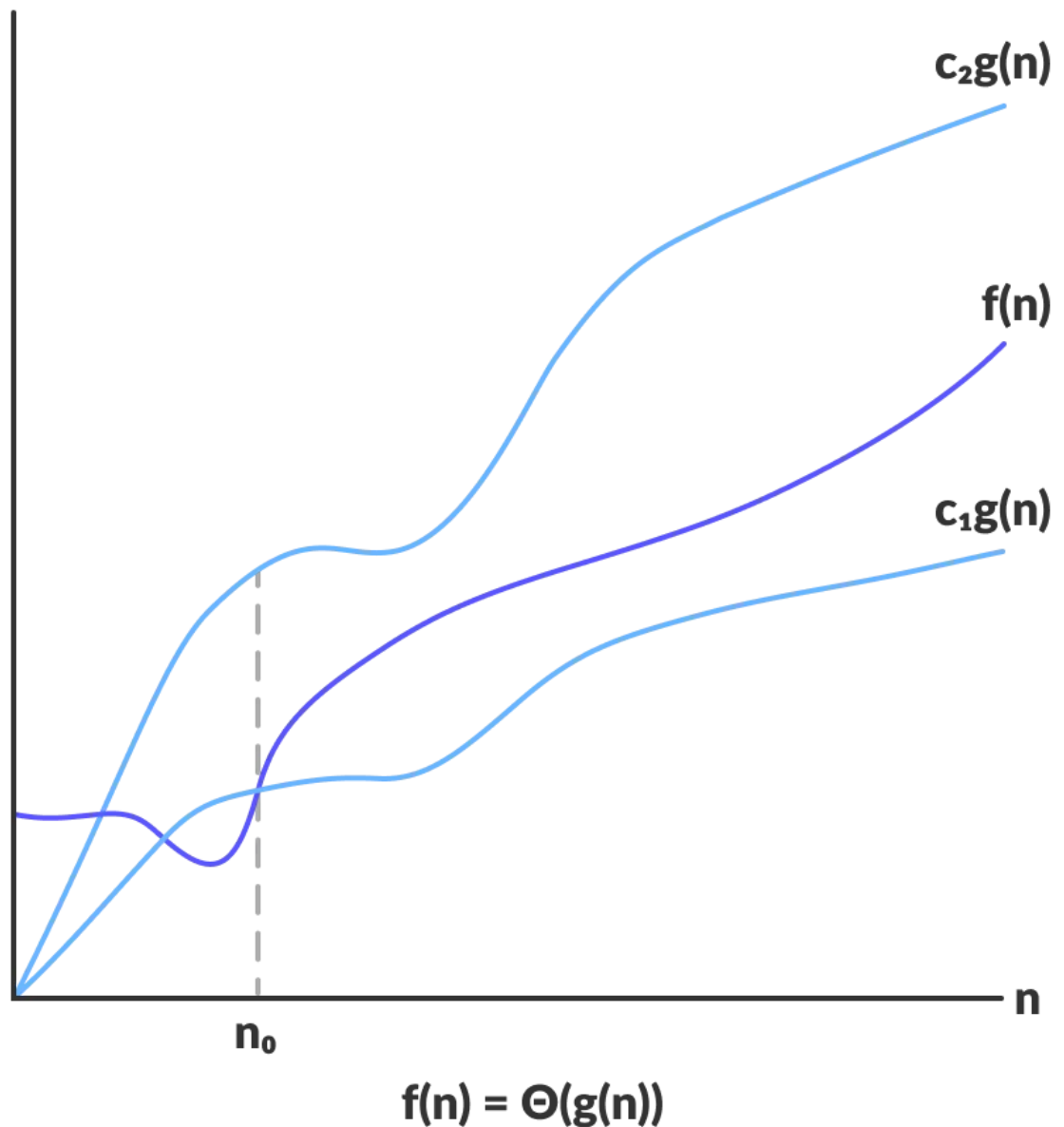
$$\Omega(g(n)) = \{ f(n) : \text{there exist positive constants } c \text{ and } n_0 \text{ such that } 0 \leq cg(n) \leq f(n) \text{ for all } n \geq n_0 \}$$

The above expression can be described as a function $f(n)$ belongs to the set $\Omega(g(n))$ if there exists a positive constant c such that it lies above $cg(n)$, for sufficiently large n .

For any value of n , the minimum time required by the algorithm is given by Omega $\Omega(g(n))$.

Theta Notation (Θ -notation)

Theta notation encloses the function from above and below. Since it represents the upper and the lower bound of the running time of an algorithm, it is used for analyzing the average-case complexity of an algorithm.



Theta bounds the function within constants factors

For a function $g(n)$, $\Theta(g(n))$ is given by the relation:

$$\Theta(g(n)) = \{ f(n) : \text{there exist positive constants } c_1, c_2 \text{ and } n_0 \text{ such that } 0 \leq c_1g(n) \leq f(n) \leq c_2g(n) \text{ for all } n \geq n_0 \}$$

The above expression can be described as a function $f(n)$ belongs to the set $\Theta(g(n))$ if there exist positive constants c_1 and c_2 such that it can be sandwiched between $c_1g(n)$ and $c_2g(n)$, for sufficiently large n .

If a function $f(n)$ lies anywhere in between $c_1g(n)$ and $c_2g(n)$ for all $n \geq n_0$, then $f(n)$ is said to be asymptotically tight bound.

Types of Time Complexity Functions

- Constant Time Complexity: $O(1)$
- Linear Time Complexity: $O(n)$
- Logarithmic Time Complexity: $O(\log n)$
- Quadratic Time Complexity: $O(n^2)$
- Exponential Time Complexity: $O(2^n)$

memory/processor is constant

```
In [29]: 1 li = [1, 2, 3, 4, 5]
          2
          3 # 1st time -> 1 sec
          4 print(li[2]) #O(1)
```

3

```
In [ ]: 1 for i in li:
          2     print(i) # O(N)
```

```
In [30]: 1 # Logarithmic Time Complexity: O(Log n)
          2 li = [1, 2, 3, 4, 5]
          3
          4 for i in range(0, len(li), 2): # O(Log n)
          5     print(li[i], i)
```

1 0

3 2

5 4

```
In [35]: 1 # Quadratic Time Complexity: O(n^2)
          2 mat = [[1,2,3],
          3           [4,5,6]]
          4
          5 # [5, 6, 7], [6, 7, 8], ...
          6 # O(N^2)
          7 for i in range(len(mat)):
          8     for j in range(len(mat[i])):
          9         print(mat[i][j] + mat[i][j], end = '\t')
         10     print()
```

2 4 6

8 10 12

```
In [ ]: 1 # Exponential Time Complexity: O(2^n)
          2
          3 2 sec
          4 4 sec
          5 8 sec
          6 16 sec
```

```
In [ ]: ▶ 1 li = [1,2,3,4,5]
          2
          3
          4 print(li[2]) -> o(1)
          5 5
          6 li.index(5) O(N)
          7
```

5 Rules

No	Description	Complexity
Rule 1	Any assignment statements and if statements that are executed once regardless of the size of the problem	$O(1)$
Rule 2	A simple “for” loop from 0 to n (with no internal loops)	$O(n)$
Rule 3	A nested loop of the same type takes quadratic time complexity	$O(n^2)$
Rule 4	A loop, in which the controlling parameter is divided by two at each step	$O(\log n)$
Rule 5	When dealing with multiple statements, just add them up	

```
In [ ]: ▶ 1 print(5) --> O(1)
          2 for i range(5):
          3     print(i)    --> o(n)
          4
          5 for i in range(5):
          6     for j in range(5):
          7         print(i, j)    --> o(n^2)
```