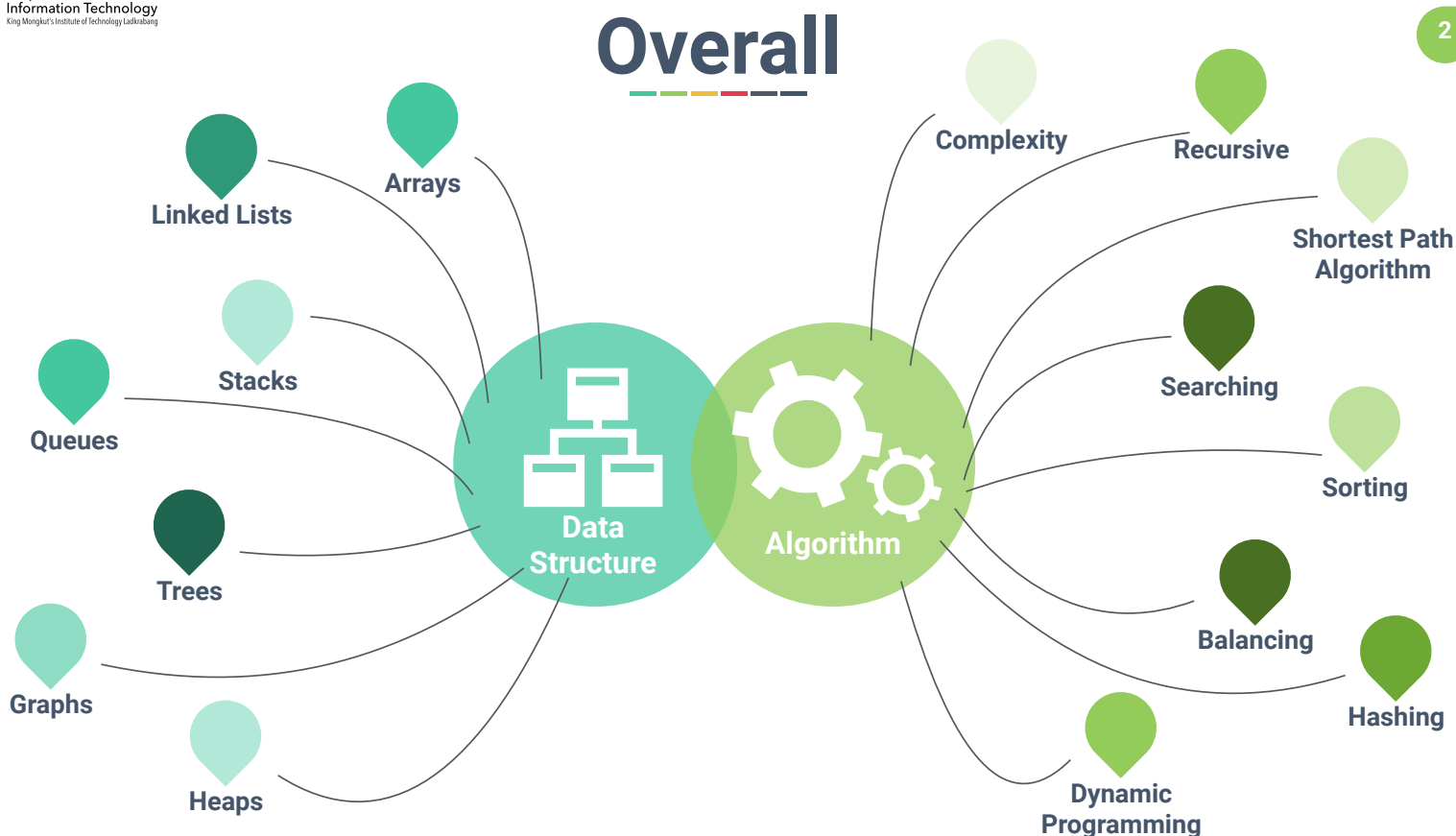


Introduction to Data Structures and Algorithms

Dr. Sirasit Lochanachit



Overall



Overall

3



What is “Data Structure” ?

4

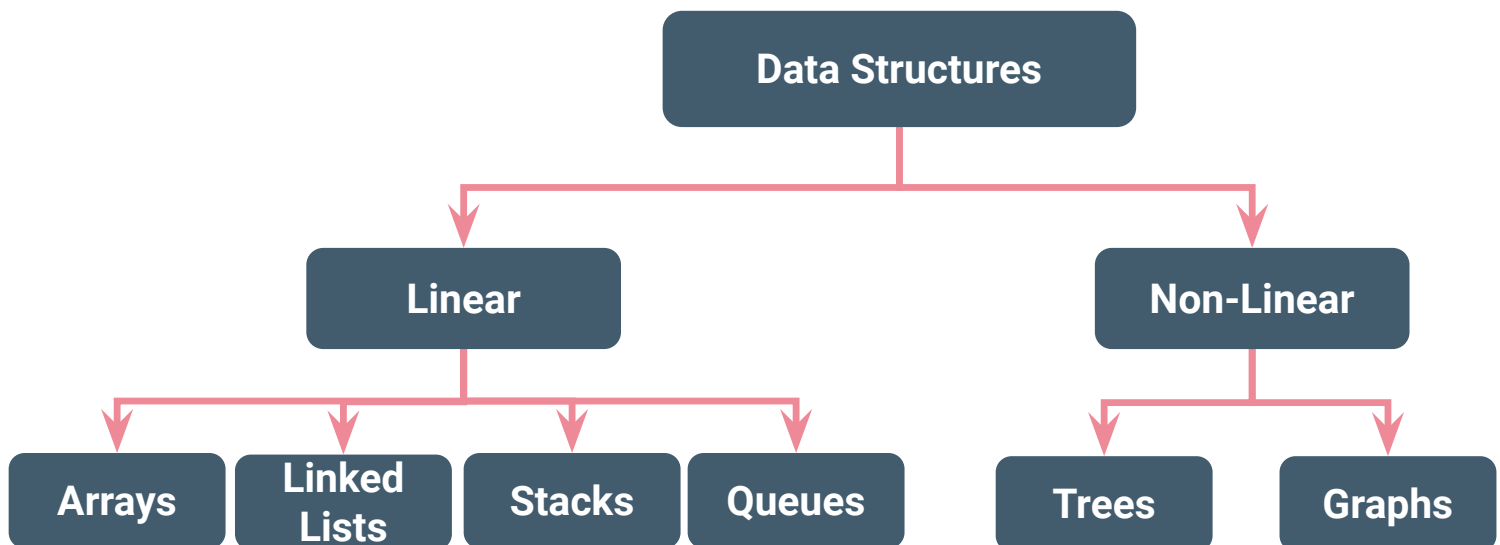


- Way to store and organise data
- Enable efficient access and modification of data
- Designed for a specific algorithm
 - Strengths and limitations
 - Time and space complexity

Abstract Data Type

- A data type, where only behavior is defined but not implementation.
- Similar to a black box where input and output are known, but not how.
- Examples: Array, List, Map, Queue, Set, and etc.

Type of Data Structure



Check out for a comprehensive list of data structures at
https://en.wikipedia.org/wiki/List_of_data_structures

What is “Algorithm” ?

7

- Well-defined procedure or set of instructions to accomplish a task
- Sequence of steps that transform input into output
- Tool to solve a well-specified computational problem

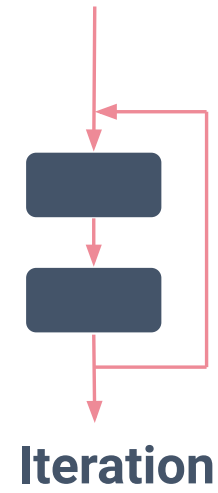
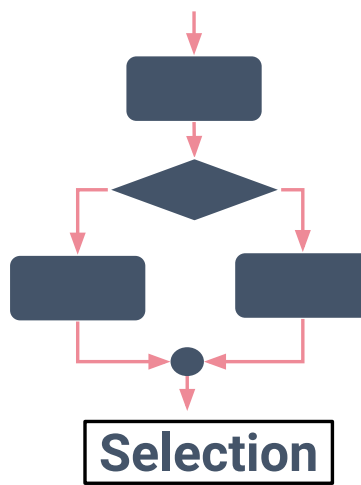
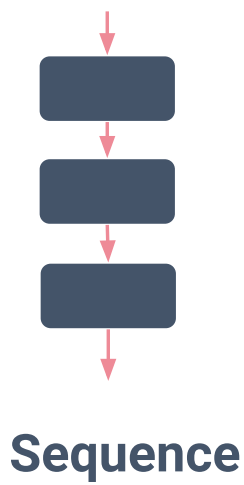


Example: Sorting numbers

8

1. Input:
 - A sequence of n numbers: $\langle a_1, a_2, \dots, a_n \rangle$
 - $\langle 31, 41, 59, 26, 41 \rangle$
2. Sorting Algorithms
3. Output:
 - A permutation (reordering) $\langle a'_1, a'_2, \dots, a'_n \rangle$ of input sequence such that $a'_1 \leq a'_2 \leq \dots \leq a'_n$
 - $\langle 26, 31, 41, 41, 59 \rangle$

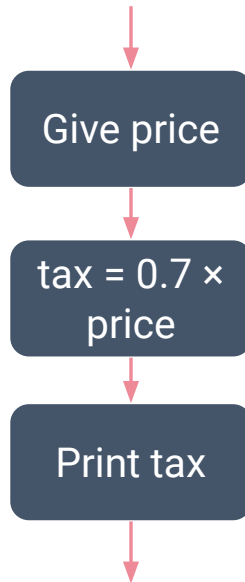
Control Structure



Sequence



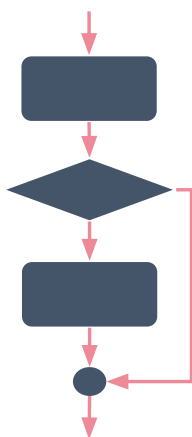
Sequence



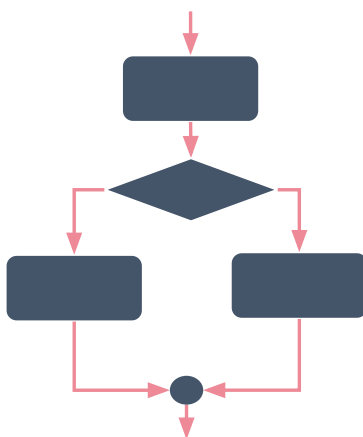
Exercise: Sequence

Write a flowchart that converts **USD currency** to **Thai baht**. At the end of the flowchart, print the **Thai baht**. (Exchange rate USD to Thai baht is 32.00)

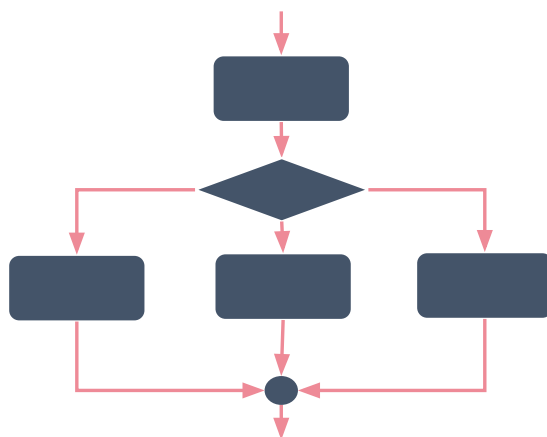
Selection



Single Selection

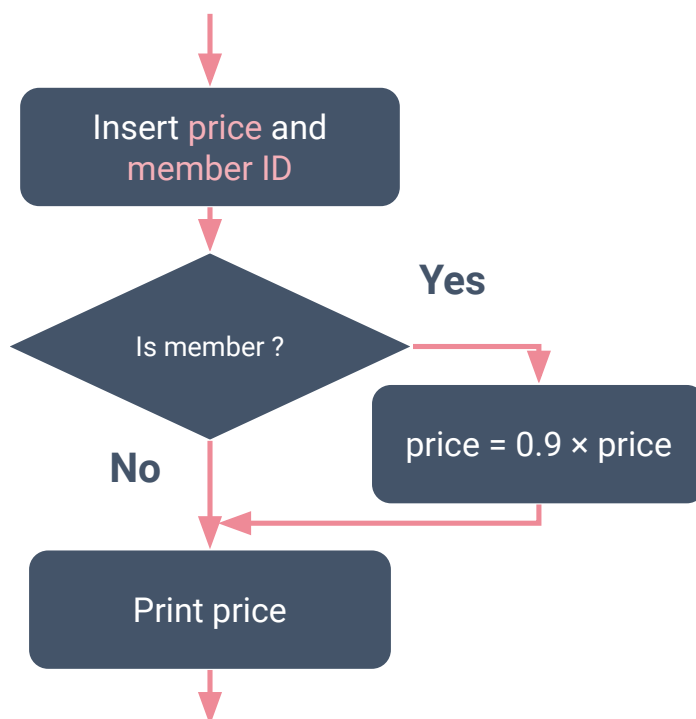


Double Selection

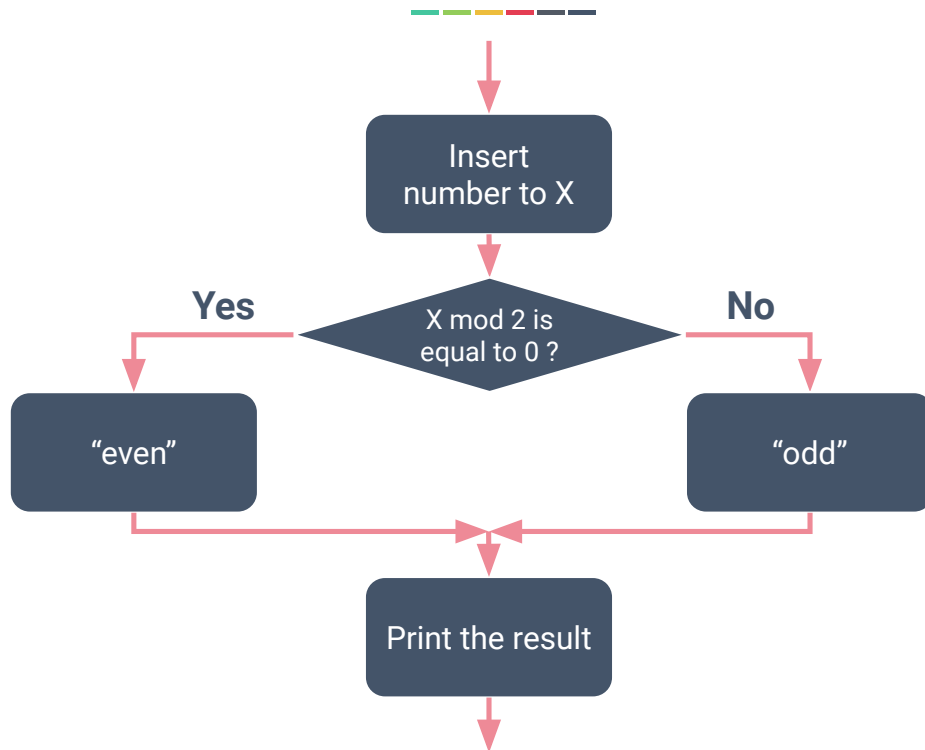


Multiple Selection

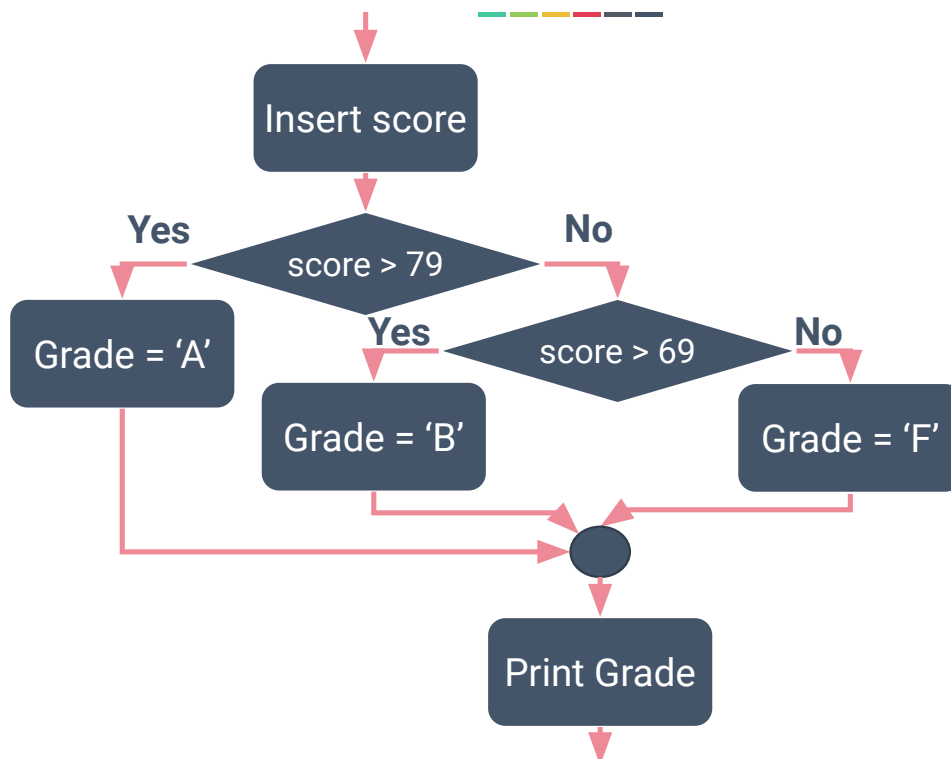
Selection



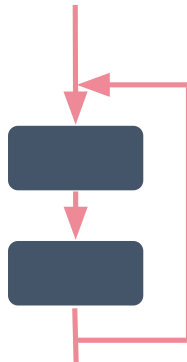
Selection



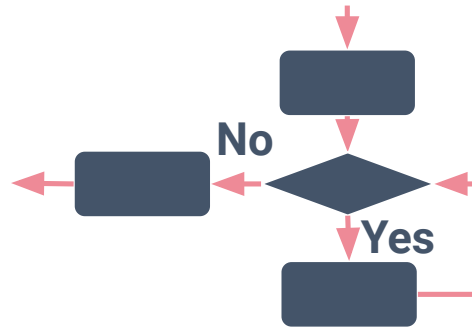
Selection



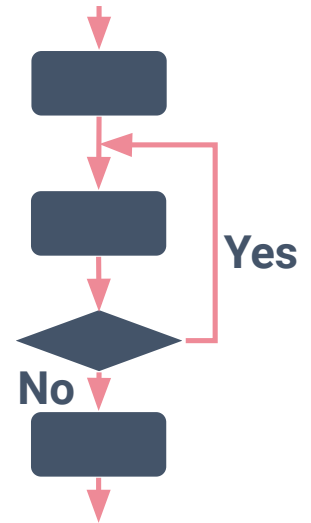
Iteration



Infinite Loop



Finite Loop



Exercise: Control Flow

Write a flowchart describing the logic of factorial function.

Hint: The factorial $n!$, is the product of all positive integers less than or equal to n .

*For example: $5! = 5 * 4 * 3 * 2 * 1 = 120$*

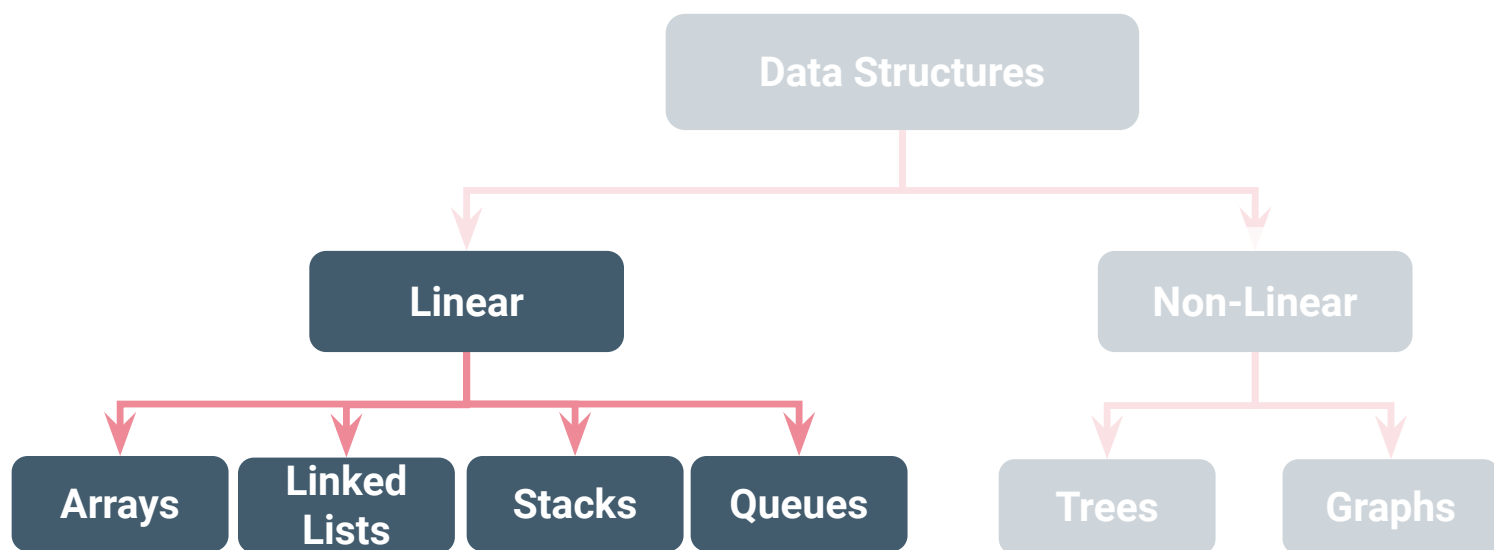
What kind of problems are solved by algorithms?

- **Human Genome Project**
 - identifying all genes of human beings
- **Internet: Routing, searches, and security**
 - Shortest path, search engines, encrypted communication
- **E-commerce**
 - Ads, recommendations, authentications
- **Commercial enterprises**
 - Resource allocation:
 - crew assignment on flights, package delivery route

Data Structures and Algorithms

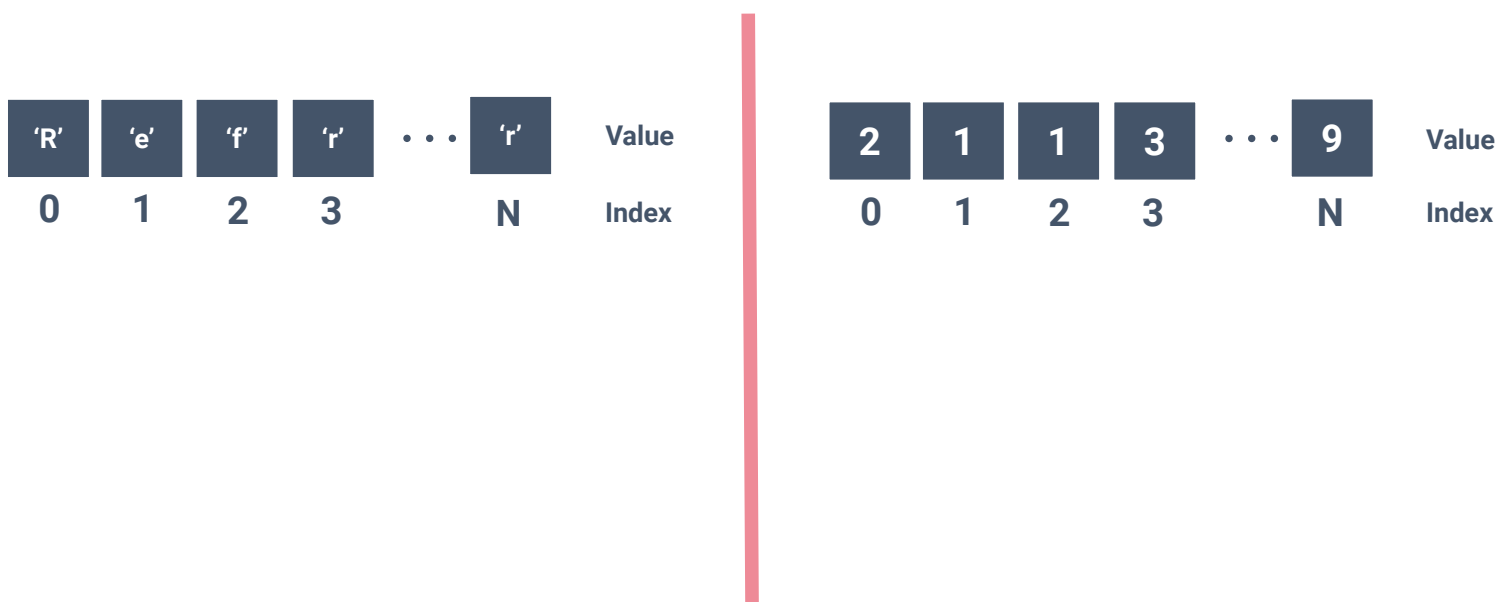
- **Data Structures**
 - Way to store and organise data
- **Algorithms**
 - Sequence of steps performed on data structures to perform a task

Type of Data Structure

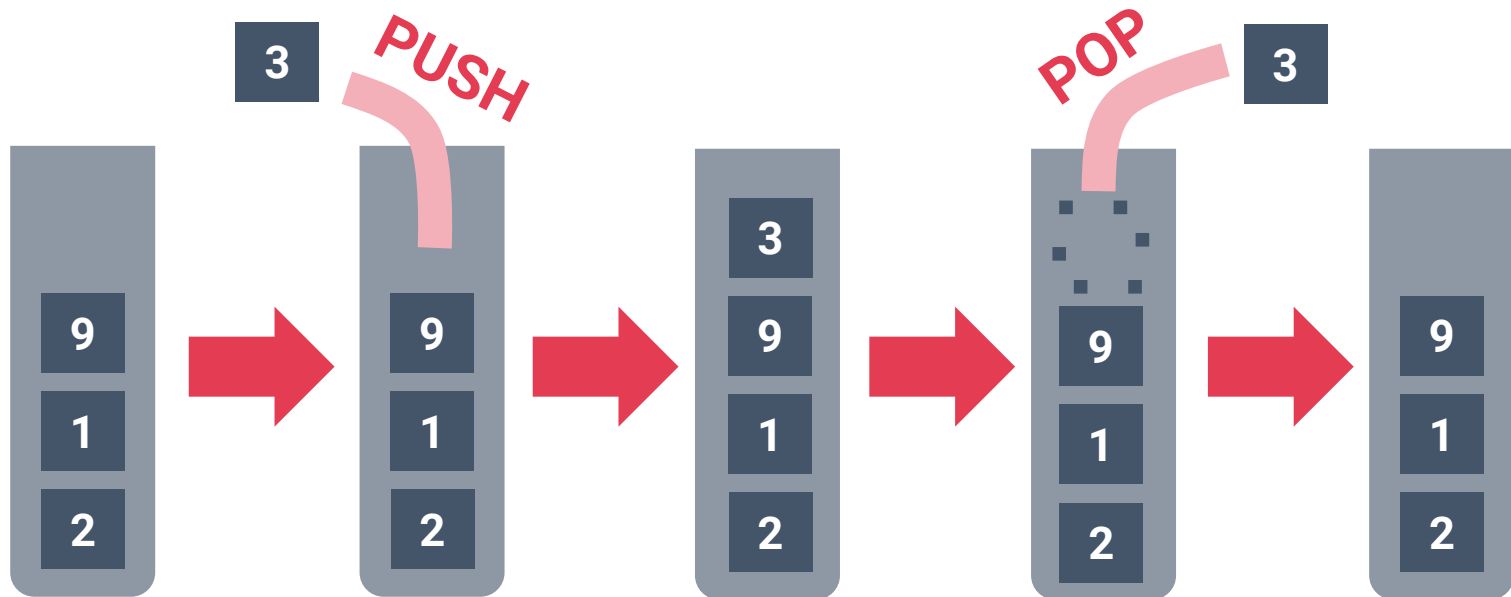


Check out for a comprehensive list of data structures at https://en.wikipedia.org/wiki/List_of_data_structures

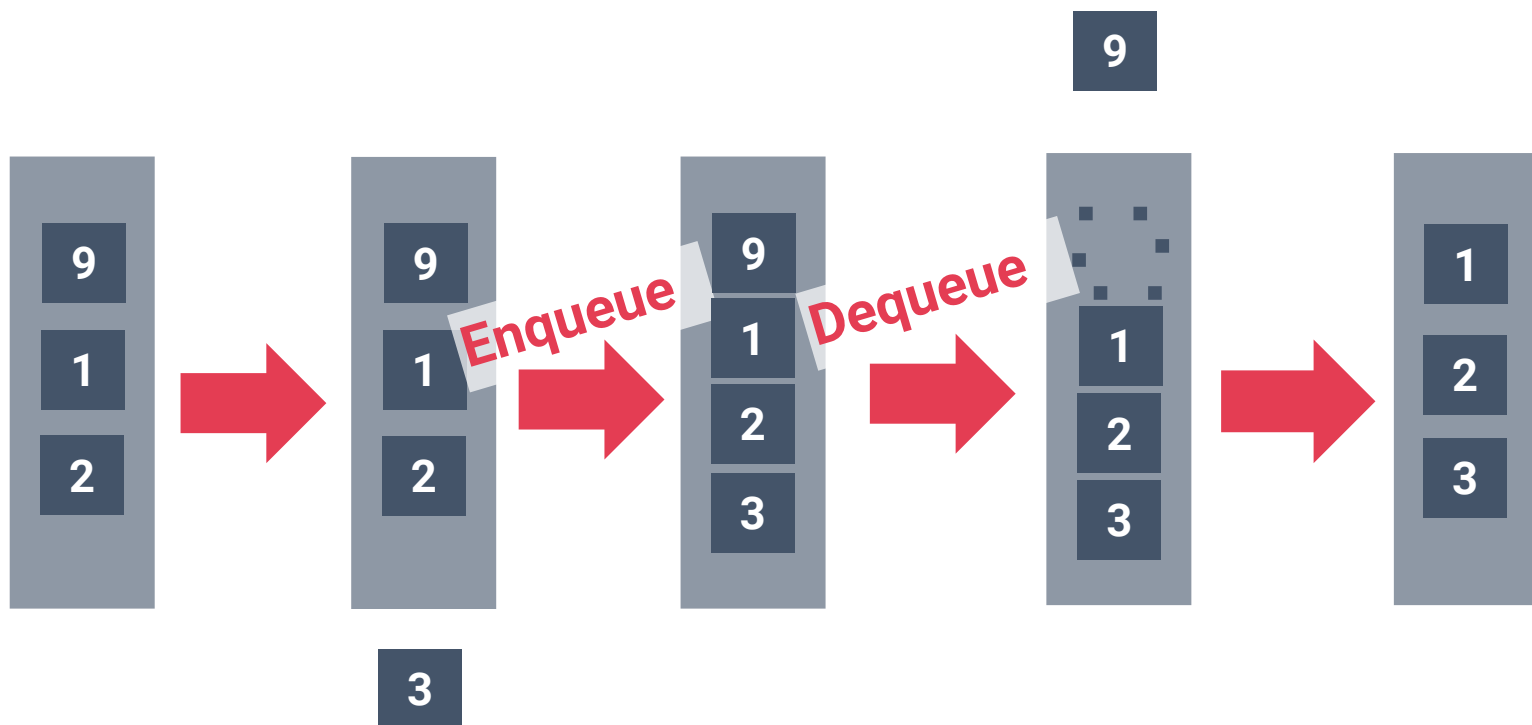
Arrays



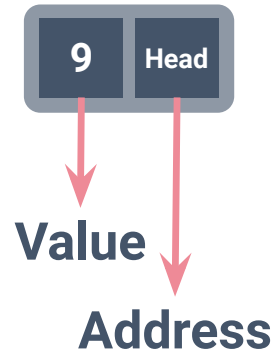
Stacks



Queues

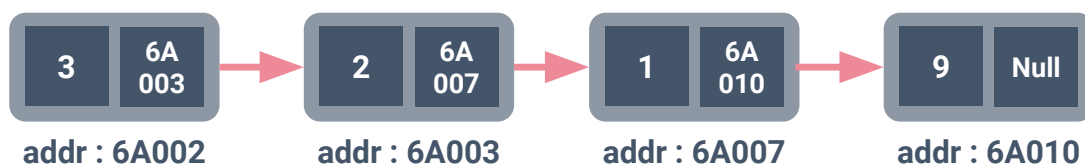


Linked Lists



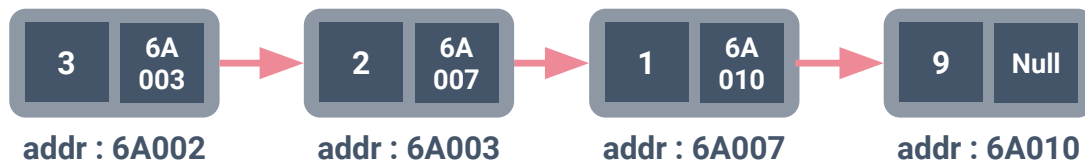
Linked Lists

• Linked Lists



Linked Lists VS Arrays

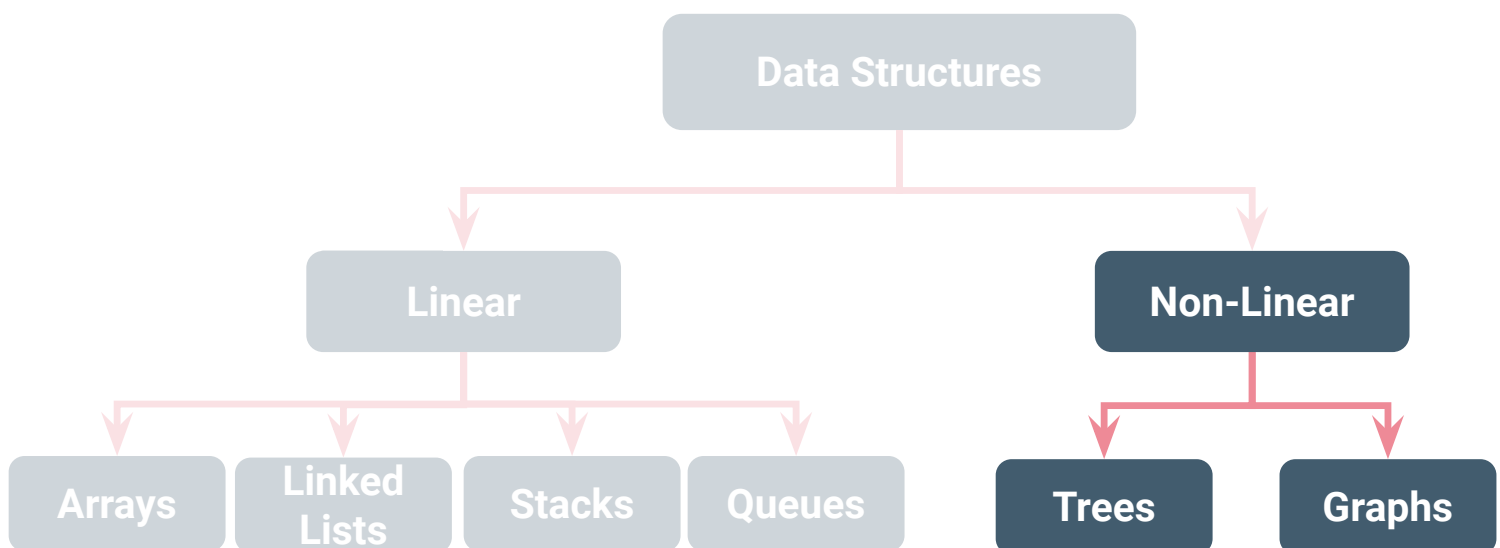
• Linked Lists



• Arrays

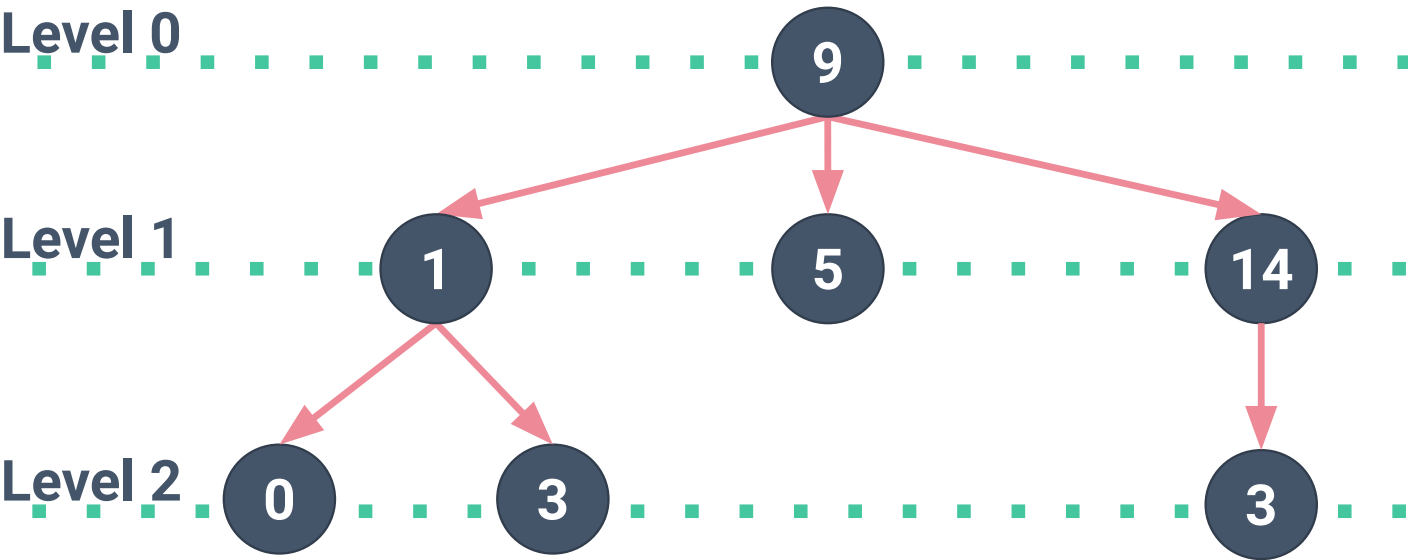


Type of Data Structure

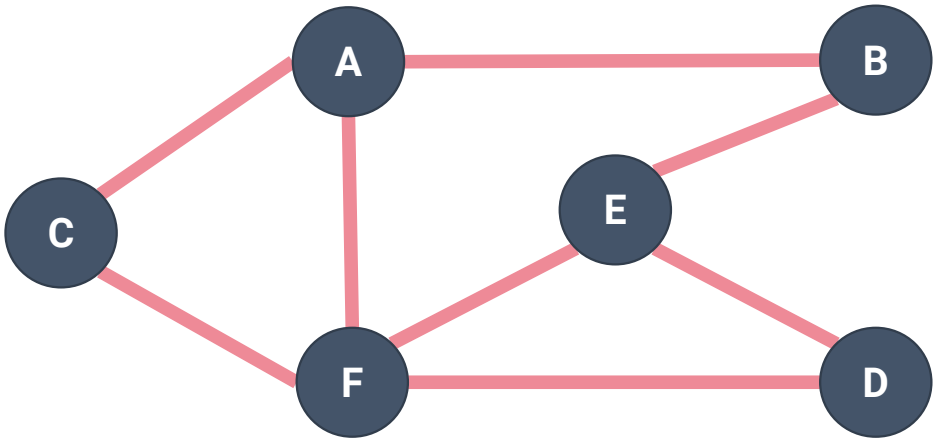


Check out for a comprehensive list of data structures at https://en.wikipedia.org/wiki/List_of_data_structures

Trees



Graphs



Algorithm Analysis



32

- If computers were infinitely fast, **any correct method** for solving a problem would do.
- Computing time and space in memory are a limited resource.
- The solution should run as fast as possible.
- For the same problem, it can be solved by different algorithms but they are often differ in their efficiency.
- **Algorithms that are efficient in terms of time or space are preferred.**

Algorithm Analysis



33

- How do we measure algorithm **efficiency** or **performance**?
 - Use **running time** as an indicator.

Benchmark Analysis

34



- Example: Summation of n integers
 - Time required for the iterative solution seems to increase as we increase the value of n .
- Running time depends on many factors
 - Hardware (CPU, RAM, etc.)
 - Software (OS, Programming language, etc.)
- Need an alternative way for analysing algorithms with respect to running time

Algorithm Analysis

35



- How do we measure algorithm **efficiency** or **performance**?
 - Use **running time** as an indicator.
- Running time can be expressed as the number of operations or steps executed.

○ theSum = 0

-> 1 step/time

○ for i in range(1,n+1):

theSum = theSum + i

-> n steps/times

Time
 complexity
 $T(n) = 1+n$



Algorithm Analysis

36

- The parameter **n** is often referred as “**size of the problem**” or **input size**
- The running time of an algorithm or data structure operation **increases** with the input size.
- Running time as a function of the input size - $f(n)$
- As n gets larger, the constant will become less significant.
- **Order of magnitude/growth** describes the running time that is most important.

Asymptotic Notation

37

- Example:
 - Suppose an algorithm runs on an input size n .
 - Times required to execute is $T(n) = 2n^2 + n + 1$
 - The n^2 terms become **larger** when n gets larger.
 - The running time of this algorithm grows as n^2 .
- Asymptotic notation represents algorithm's complexity
 - Ignores constant factors and slower growing terms.
 - Focus on the main components that affect the growth.
 - **Big-O notation**

Big-O notation



•Big-O notation (Order)

• Example:

- Given $T(n) = 1+n$, then $T(n) = O(n)$
- Given $T(n) = 2n^2 + n + 1$, then $T(n) = O(n^2)$

• $O(n)$ means time complexity will never exceed n .

Big-O notation



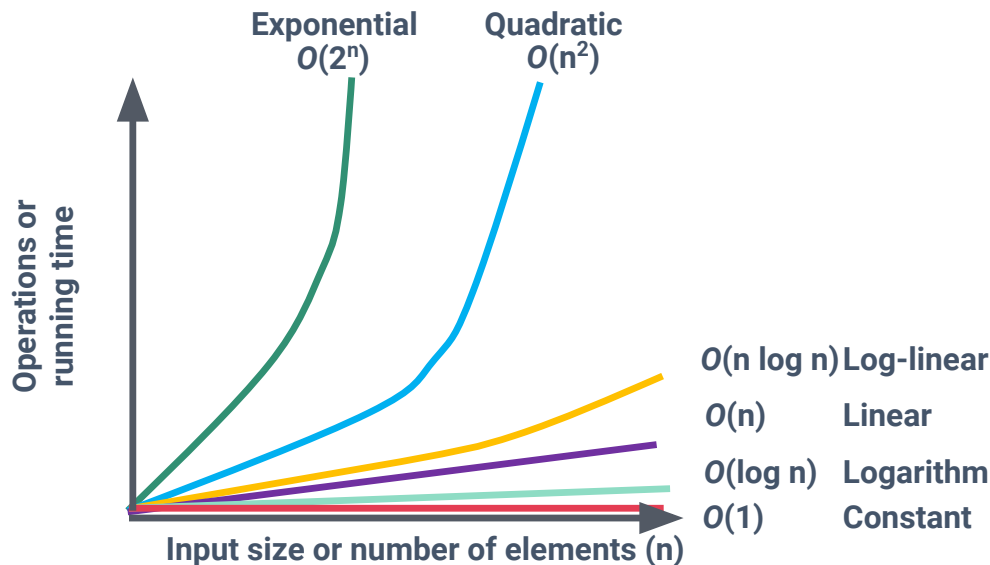
•Big-O notation (Order)

• Common $f(n)$:

- $O(1)$: constant
- $O(\log n)$: logarithm
- $O(n)$: Linear
- $O(n \log n)$: Log linear
- $O(n^2)$: Quadratic
- $O(2^n)$: Exponential
- $O(n!)$: Factorial

Time Complexity

In general, **the standard functions** of input size n are shown in figure.

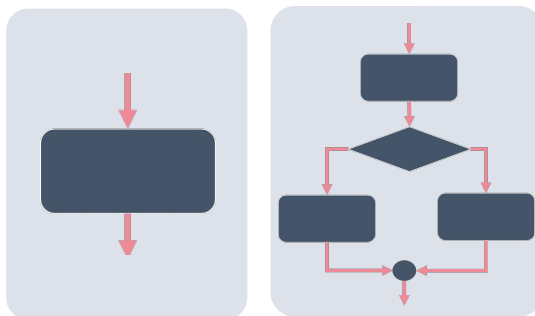


Calculating Time Complexity

Mathematic

$$f(n) = 3$$

Computer



- Simple statements (read, write, assign)
- Simple operations (+ - * / == > >= < <=)

Big-O

$$O(1)$$

Constant

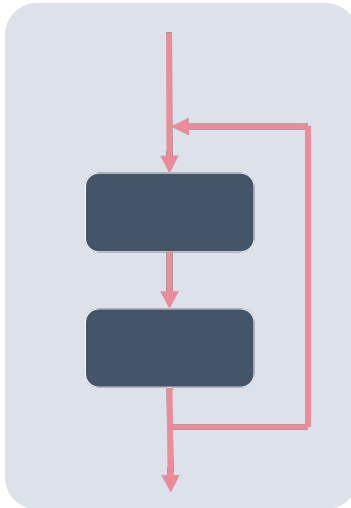
Calculating Time Complexity

Mathematic

$$f(n) = n-3$$

Computer

Linear loop



Big-O

$$O(n)$$



Linear

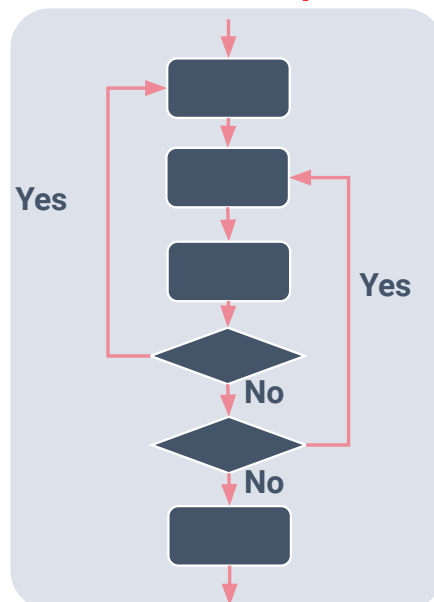
Calculating Time Complexity

Mathematic

$$f(n) = n^2 + n + 7$$

Computer

Nested loop



Big-O

$$O(n^2)$$



Quadratic

Loops

Python Code

Time complexity

Linear

```
for i in range (0,n):
    do something
```



$T(n) = n, O(n)$

Linear

```
for i in range (0,n/2):
    do something
```



$T(n) = n/2, O(n)$

Nested

```
for i in range (0,n):
    for j in range (0,n):
        do something
```



$T(n) = n^2, O(n^2)$

Loops

Python Code

Time complexity

Logarithmic

```
i = 1
while i < n:
    do something
    i *= 2
```



$n=1000$

1
2
4
8
16
32
64
128
256
512



$T(n) = \log n, O(\log n)$

Logarithmic

```
i = n
while i >= 1:
    do something
    i //= 2
```



1000
500
250
125
62
31
15
7
3
1



$T(n) = \log n, O(\log n)$

Loops

Python Code

Time complexity

**Linear
logarithmic**

```
for i in range (0,n):
    j = 1
    while j < n:
        do something
        j *= 2
```



$T(n) = n \log n, O(\textcolor{red}{n} \log n)$

Loops

Python Code

Time complexity

**Dependent
Nested**

```
for i in range (0,n):
    for j in range(0, i+1)
        do something
```



$T(n) = n(n+1)/2, O(\textcolor{red}{n}^2)$

Number of iterations of the inner loop depends on the outer loop

For the inner loop, the number of iterations is $(n+1)/2$

Exercise

48

Time complexity

- $n^2 + 100n$
- $n^2 * n + 100n^2 \log n$
- $123 + \log 657$
- $(n + \log n)^3$
- $n(2 + \log n)$
- $1 + 2 + 3 + \dots + n$



$O(?)$
 $O(?)$
 $O(?)$
 $O(?)$
 $O(?)$
 $O(?)$

Exercise

49

Time complexity

- $n^2 + 100n$
- $n^2 * n + 100n^2 \log n$
- $123 + \log 657$
- $(n + \log n)^3$
- $n(2 + \log n)$
- $1 + 2 + 3 + \dots + n$



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

Calculating Time Complexity

Python Code: Factorial

```
def factorial1(n):
```

```
    if n <= 1:
        return 1
```

```
    else:
```

```
        fact = 1
```

```
        for i in range(2, n+1):
```

```
            fact *= i
```

```
        return fact
```

→ $T(1)$

→ $T(1)$

→ $T(n)$

→ $T(1)$

$$T(n) = 2 + n + 1 = n + 3$$

Complexity: $O(n)$

Calculating Time Complexity

Python Code: Simple nested loops

```
def simple(n):
```

```
    for i in range(n):
```

```
        for j in range(n):
```

```
            print("i: {0}, j: {1}".format(i, j))
```

→ $T(n)$

→ $T(n)$

$$T(n) = n * n$$

Complexity: $O(n^2)$

Calculating Time Complexity

Python Code: Element uniqueness v1

```

def unique1(s):
    for i in range(len(s)):
        for j in range(i+1, len(s)):
            if s[i] == s[j]:
                return False # Found duplicate pair
    return True # All elements are unique
  
```

→ $T(n)$
 → $T(n)$

$$T(n) = n(n-1)/2$$

Complexity: $O(n^2)$

Calculating Time Complexity

Python Code: Element uniqueness v2

```

def unique2(s):
    temp = sorted(s) # create a sorted copy of s
    for i in range(1, len(temp)):
        if temp[i-1] == temp[i]:
            return False # Found duplicate pair
    return True # All elements are unique
  
```

→ $T(n \log n)$
 → $T(n)$

$$T(n) = n \log n + n$$

Complexity: $O(n \log n)$

Calculating Time Complexity

Python Code: Prefix averages v1

```
def prefix_average1(s):
    n = len(s)
    a = [0] * n          # create list of n zeros
    for i in range(n):
        total = 0         # compute each element
        for j in range(i+1):
            total += s[j]
        a[i] = total / (i+1) # record the average
    return a
```

→ $T(1)$

→ $T(n)$

→ $T(n)$

→ $T(n)$

$$T(n) = 1 + n + 2n + \frac{n(n+1)}{2}$$

Complexity: $O(n^2)$

Calculating Time Complexity

Python Code: Prefix averages v2

```
def prefix_average2(s):
    n = len(s)
    a = [0] * n          # create list of n zeros
    for i in range(n):
        a[i] = sum(s[0:i+1]) / (i+1) # record the average
    return a
```

→ $T(1)$

→ $T(n)$

→ $T(n)$

→ $T(n)$

$$T(n) = 1 + n + \frac{n(n+1)}{2}$$

Complexity: $O(n^2)$

Calculating Time Complexity

Python Code: Prefix averages v3

```
def prefix_average3(s):
    n = len(s)
    a = [0] * n          # create list of n zeros
    total = 0
    for i in range(n):
        total += s[i]    # update total sum to include s[i]
        a[i] = total / (i+1) # compute average based on
                           # current sum
    return a
```

→ $T(1)$
→ $T(n)$
→ $T(1)$

→ $T(n)$

$T(n) = 2 + n + 2n$

v3 is asymptotically better than v2 and v1 **Complexity: $O(n)$**

Exercise 1

Python Code

```
def example1(s):
    n = len(s)
    total = 0
    for i in range(n):    # loop from 0 to n-1
        total += s[i]
    return total
```

Complexity: $O(?)$

Exercise 2

Python Code

```
def example2(s):  
    n = len(s)  
    total = 0  
    for i in range(0,n,2): # Increment of 2  
        total += s[i]  
    return total
```

Complexity: $O(?)$

Exercise 3

Python Code

```
def example3(s):  
    n = len(s)  
    total = 0  
    for i in range(n): # loop from 0 to n-1  
        for k in range(1+i): # loop from 0 to i  
            total += s[k]  
    return total
```

Complexity: $O(?)$

Exercise 4

Python Code

```
def example4(s):  
    n = len(s)  
    prefix = 0  
    total = 0  
    for i in range(n):  
        prefix += s[i]  
        total += prefix  
    return total
```

Complexity: $O(?)$

Exercise 5

Python Code

```
# Assume that A and B have equal length of n  
def example5(A,B):  
    n = len(A)  
    count = 0  
    for i in range(n): # loop from 0 to n-1  
        total = 0  
        for j in range(n): # loop from 0 to n-1  
            for k in range(1+j): # loop from 0 to j  
                total += A[k]  
            if B[i] == total:  
                count += 1  
    return count
```

Complexity: $O(?)$