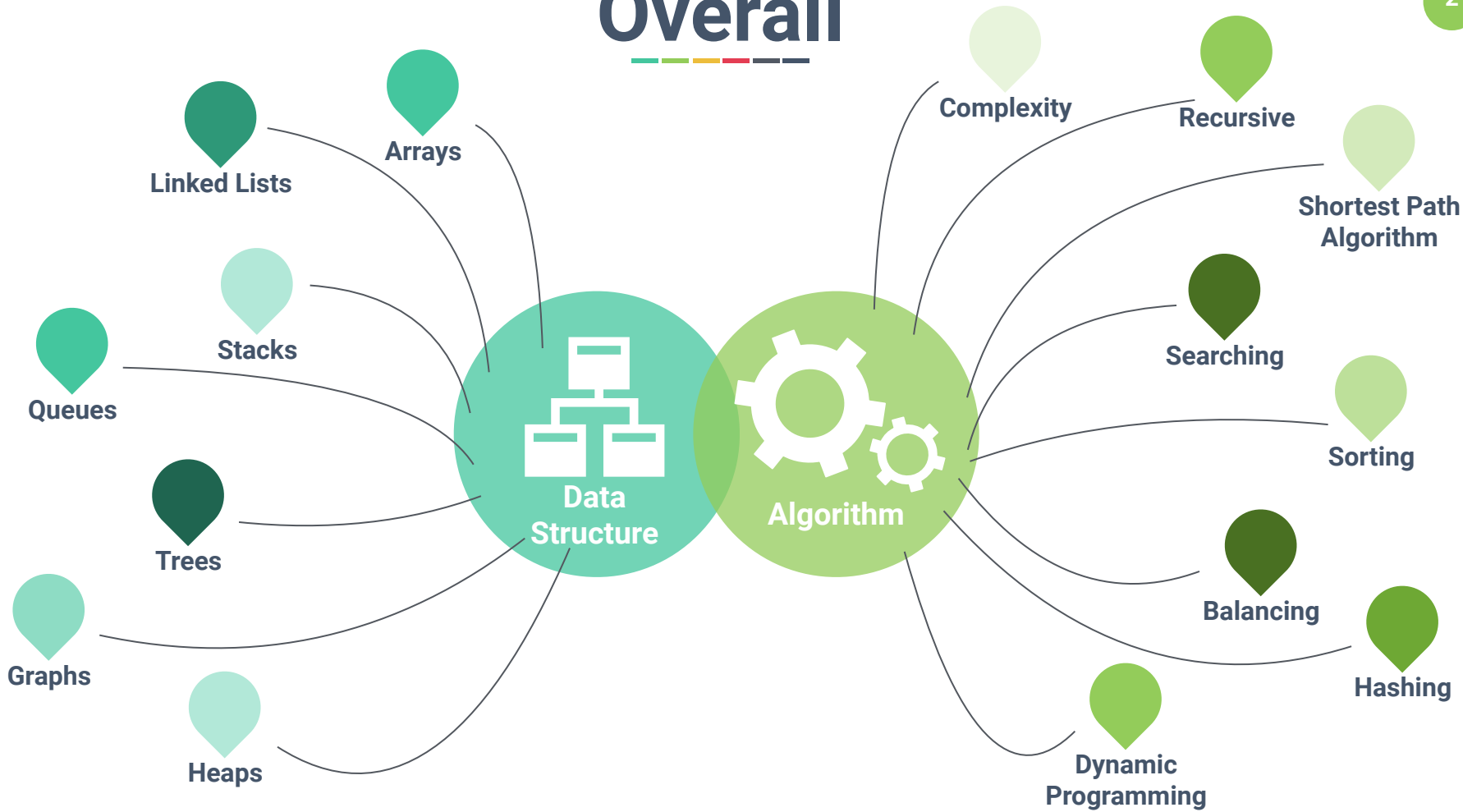


Introduction to Data Structures and Algorithms



Dr. Sirasit Lochanachit

Overall



Overall



What is “Data Structure” ?



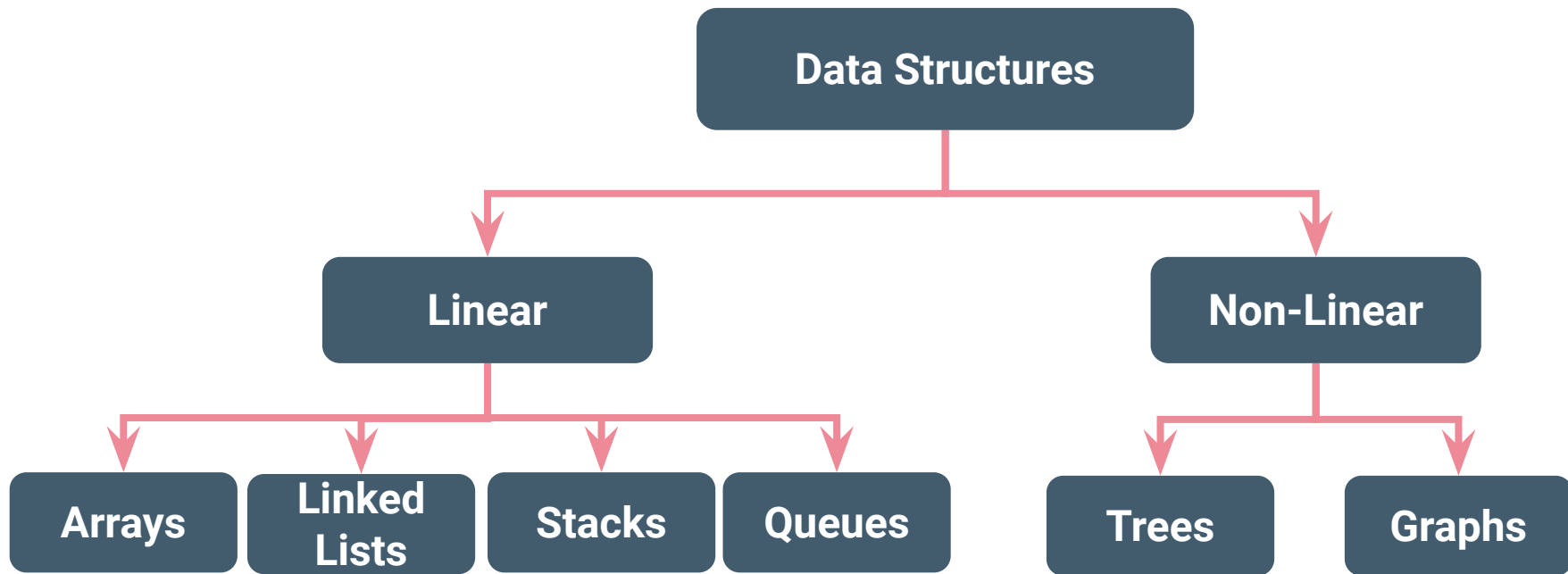
- Way to store and organise data
- Enable efficient access and modification of data
- Designed for a specific algorithm
 - Strengths and limitations
 - Time and space complexity

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” ?

- 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



1. Input:

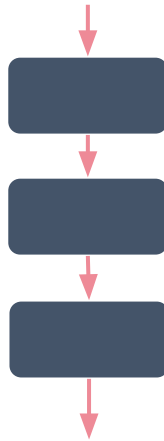
- A sequence of n numbers: $\langle a_1, a_2, \dots, a_n \rangle$
- $\langle 31, 41, 59, 26, 41 \rangle$

2. Sorting Algorithms

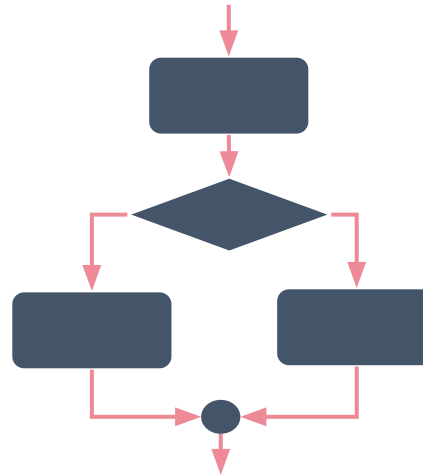
3. Output:

- A permutation (reordering) $\langle a'_1, a'_2, \dots, a'_n \rangle$
of input sequence such that $a'_1 \leq a'_2 \leq \dots \leq a'_n$
- $\langle 26, 31, 41, 41, 59 \rangle$

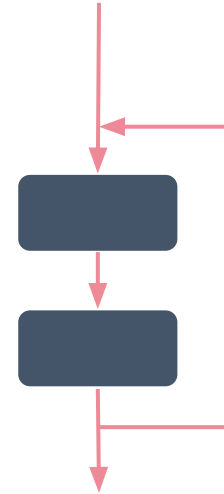
Control Structure



Sequence

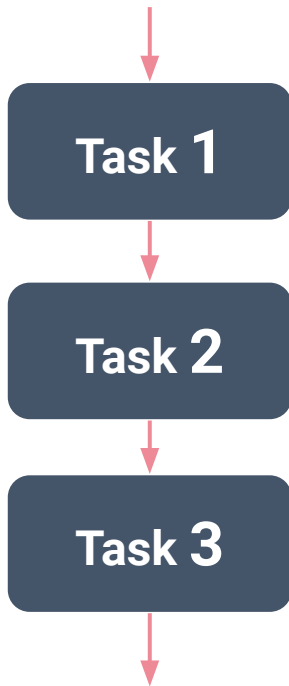


Selection

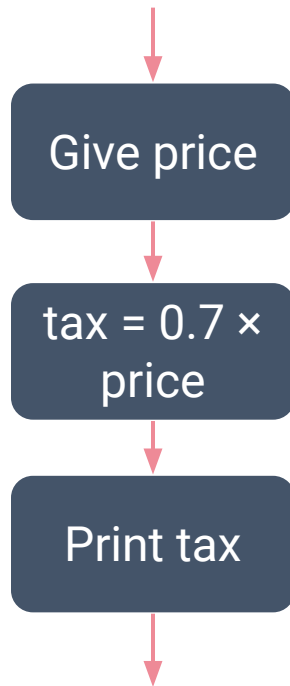


Iteration

Sequence



Sequence

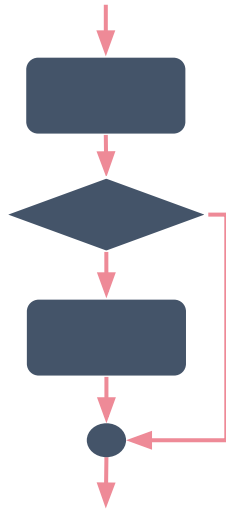


Exercise: Sequence

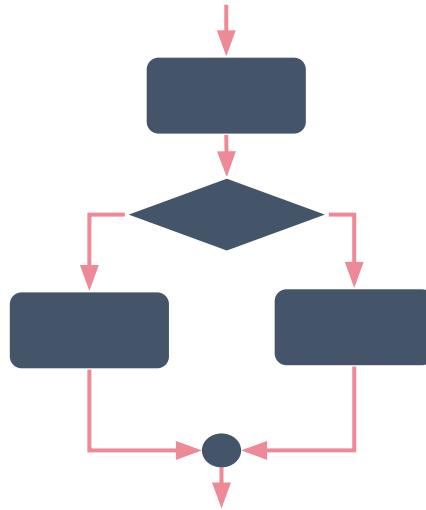


Write a flowchart that converts **USD currency** to **Thai baht**. At the end of the flowchart, print the **Thai baht**. (Exchange rate USD to Thai baht is 32.00)

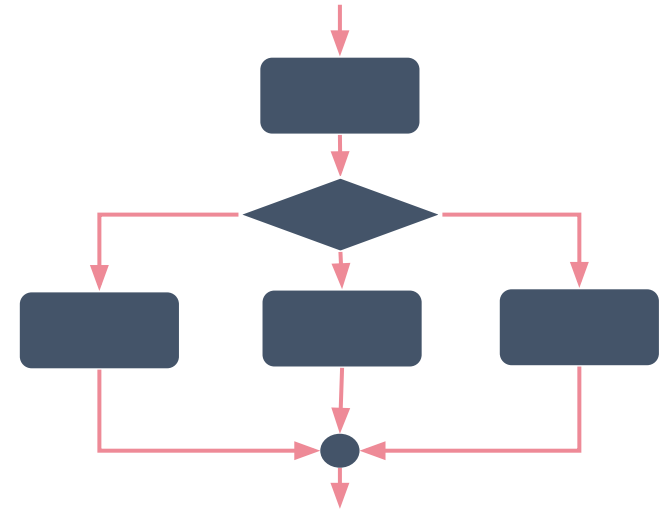
Selection



Single Selection

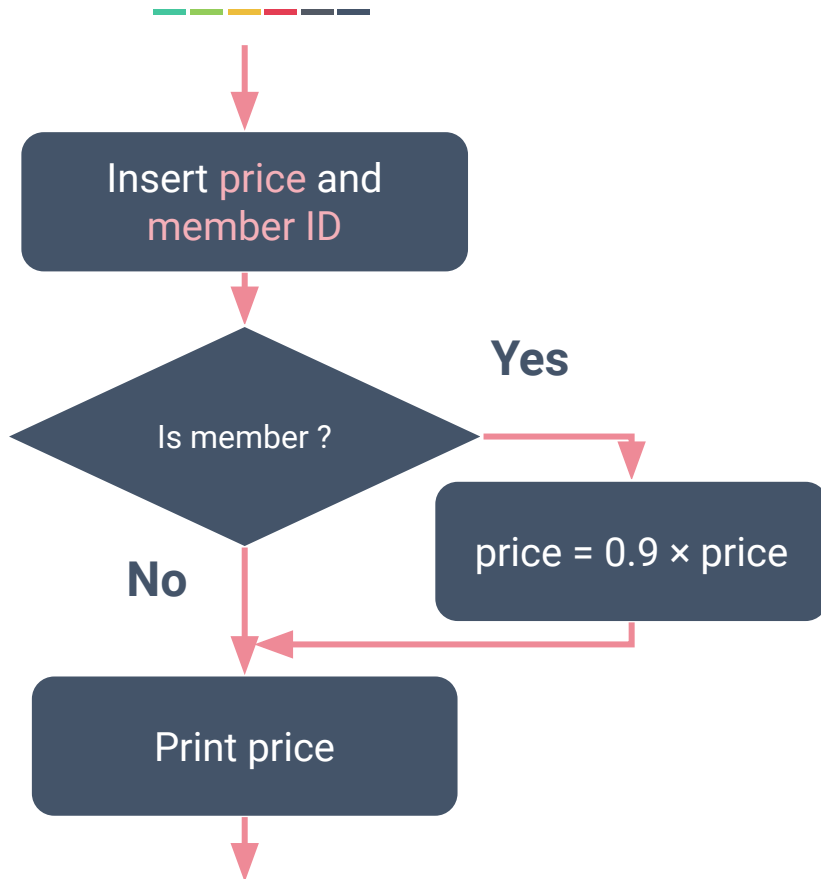


Double Selection

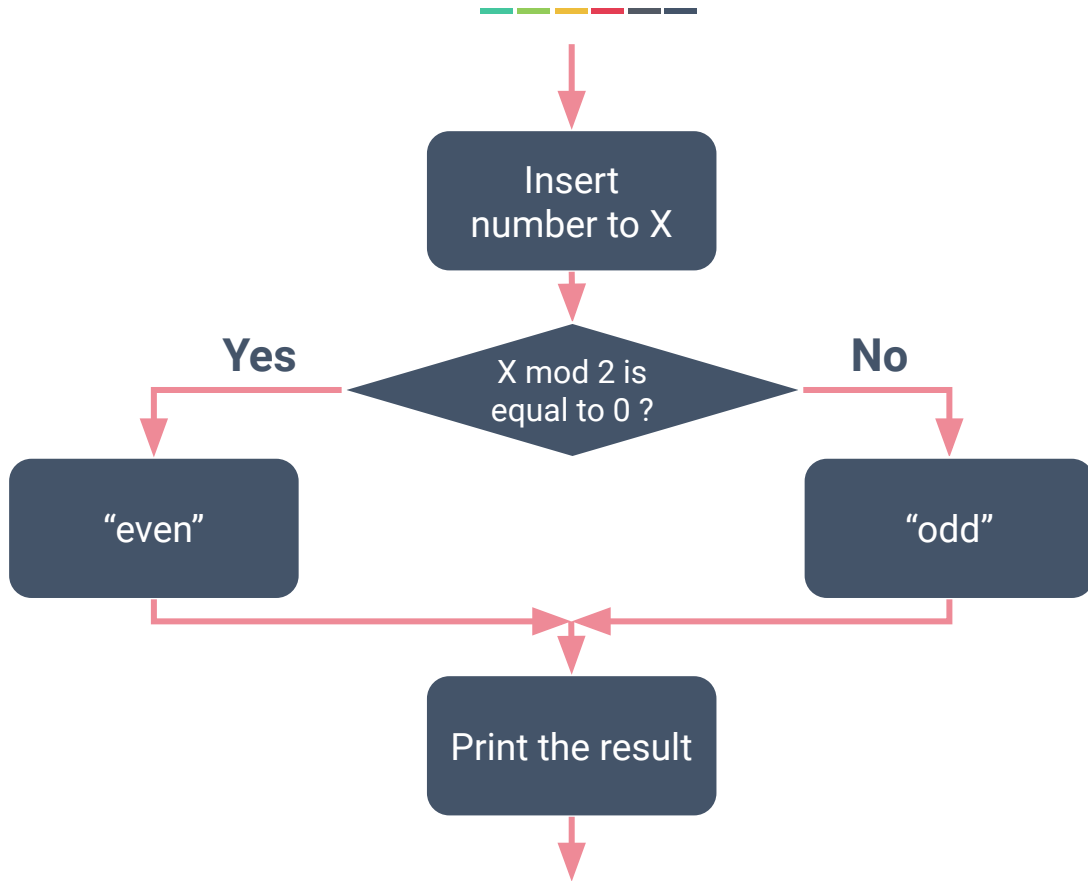


Multiple Selection

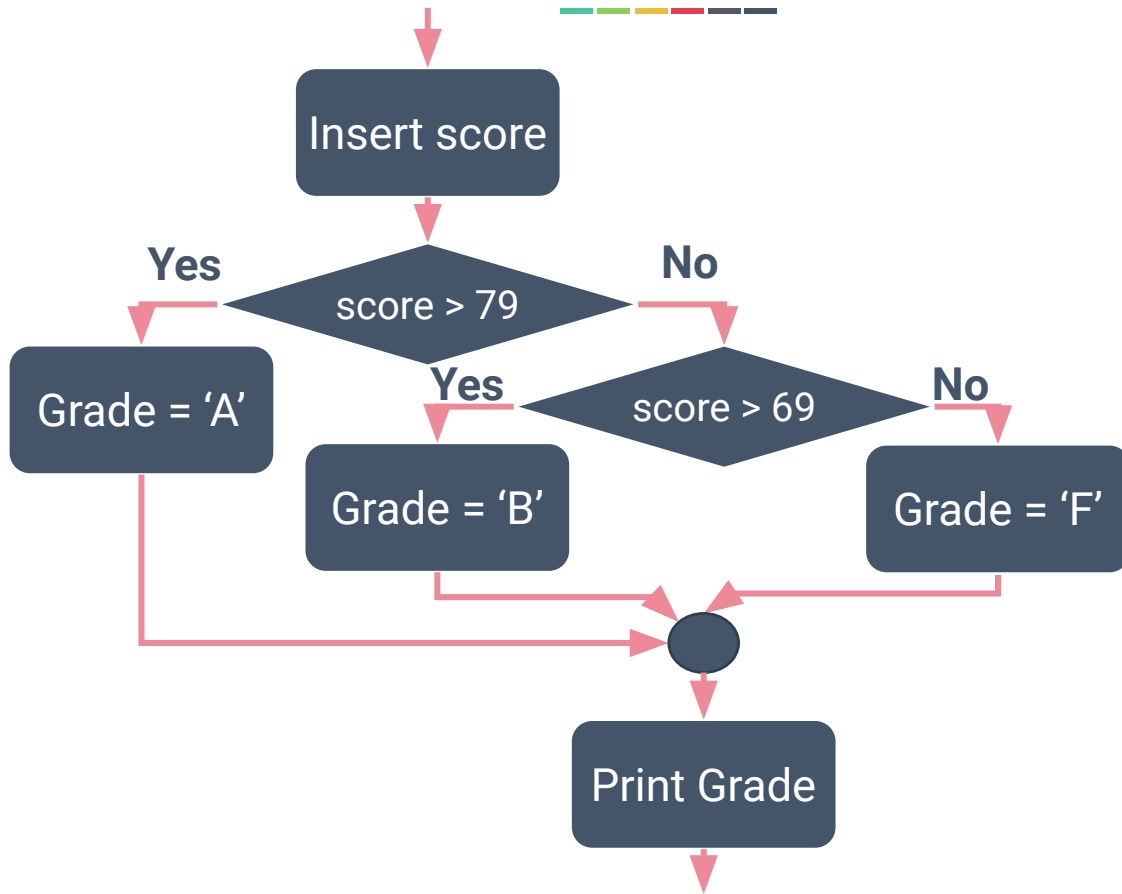
Selection



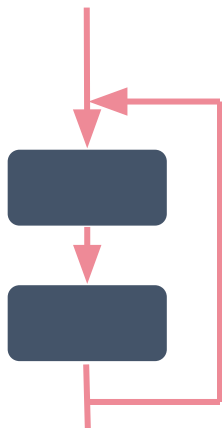
Selection



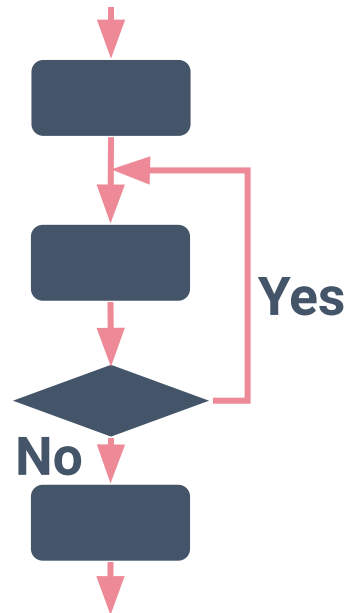
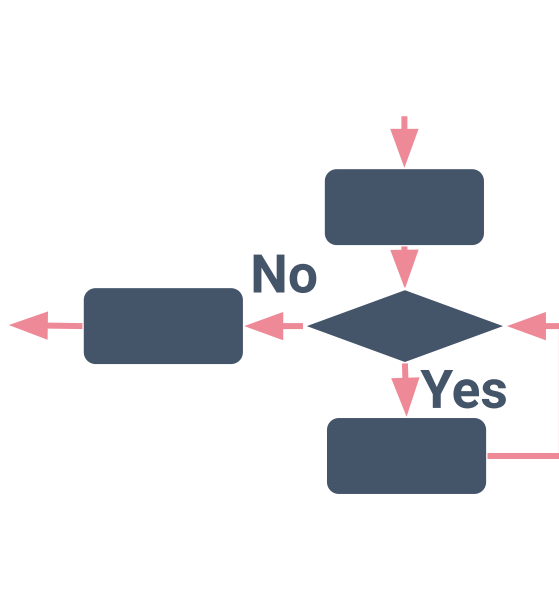
Selection



Iteration



Infinite Loop



Finite Loop

Exercise: Control Flow



Write a flowchart describing the logic of factorial function.

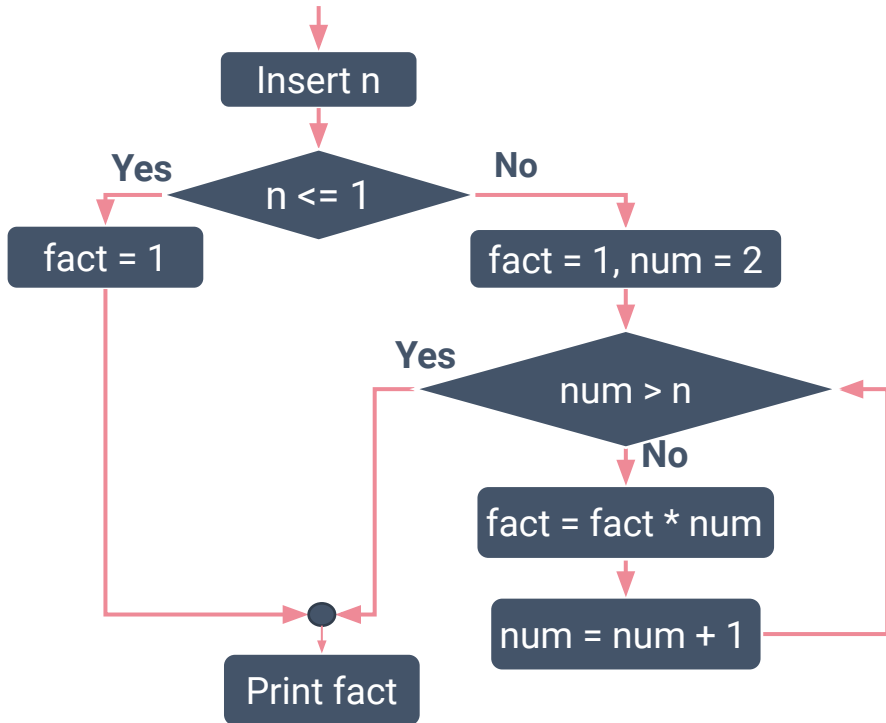
Hint: The factorial $n!$, is the product of all positive integers less than or equal to n .

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

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 .



```
def factorial1(n):  
    if n <= 1:  
        return 1  
    else:  
        fact = 1  
        for num in range(2, n+1):  
            fact *= num  
        return fact
```

What kind of problems are solved by algorithms?

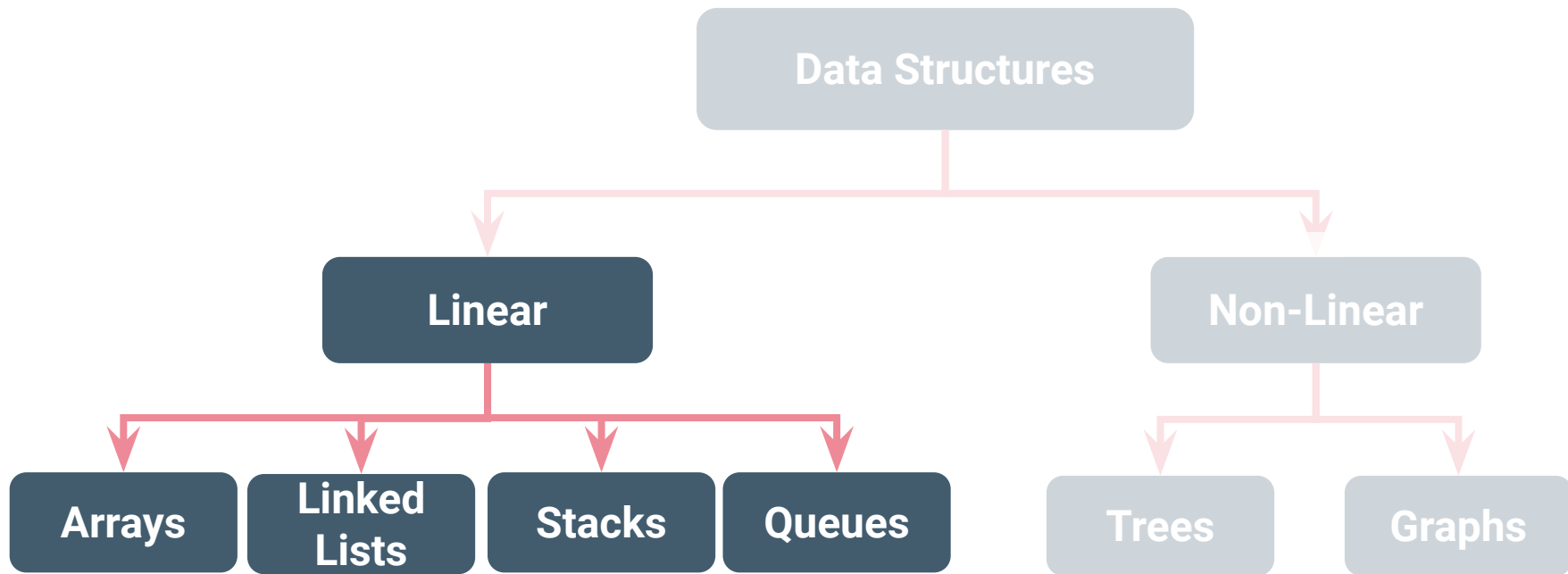
- **Human Genome Project**
 - identifying all genes of human beings
- **Internet: Routing, searches, and security**
 - Shortest path, search engines, encrypted communication
- **E-commerce**
 - Ads, recommendations, authentications
- **Commercial enterprises**
 - Resource allocation:
 - crew assignment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



Value

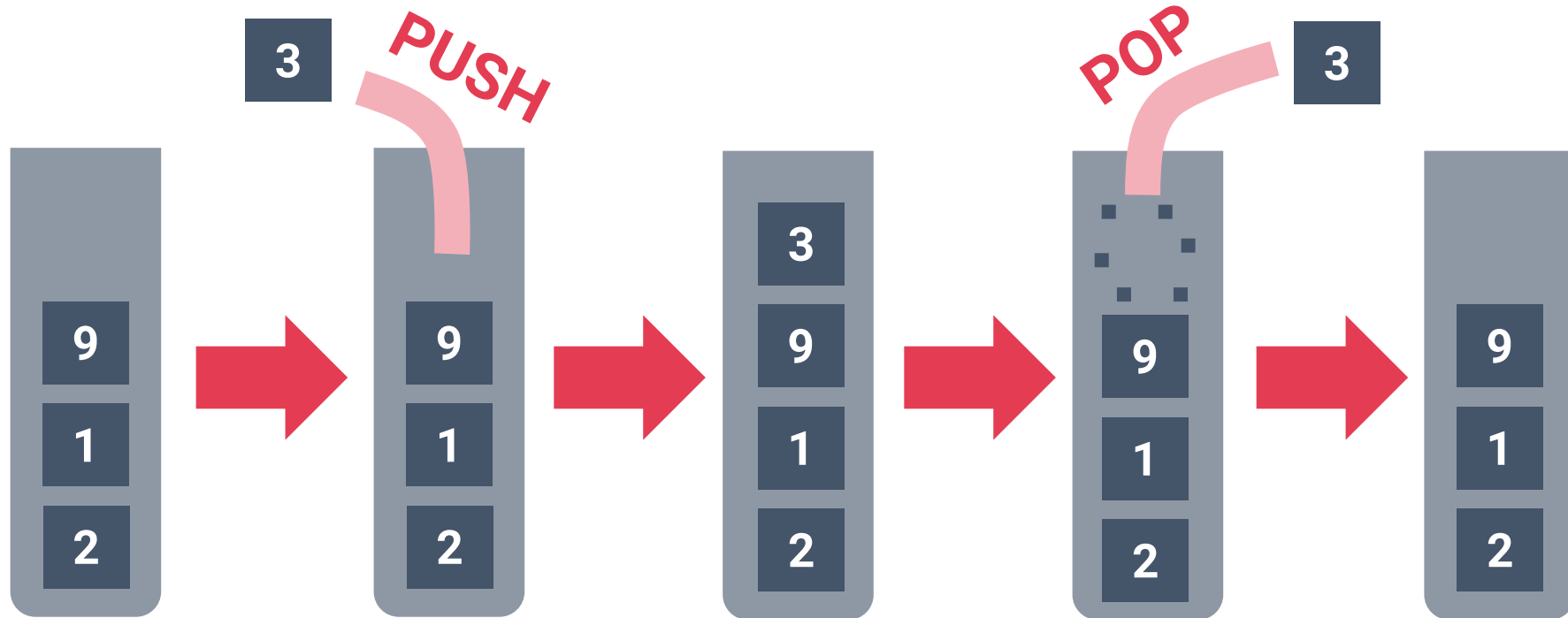
Index



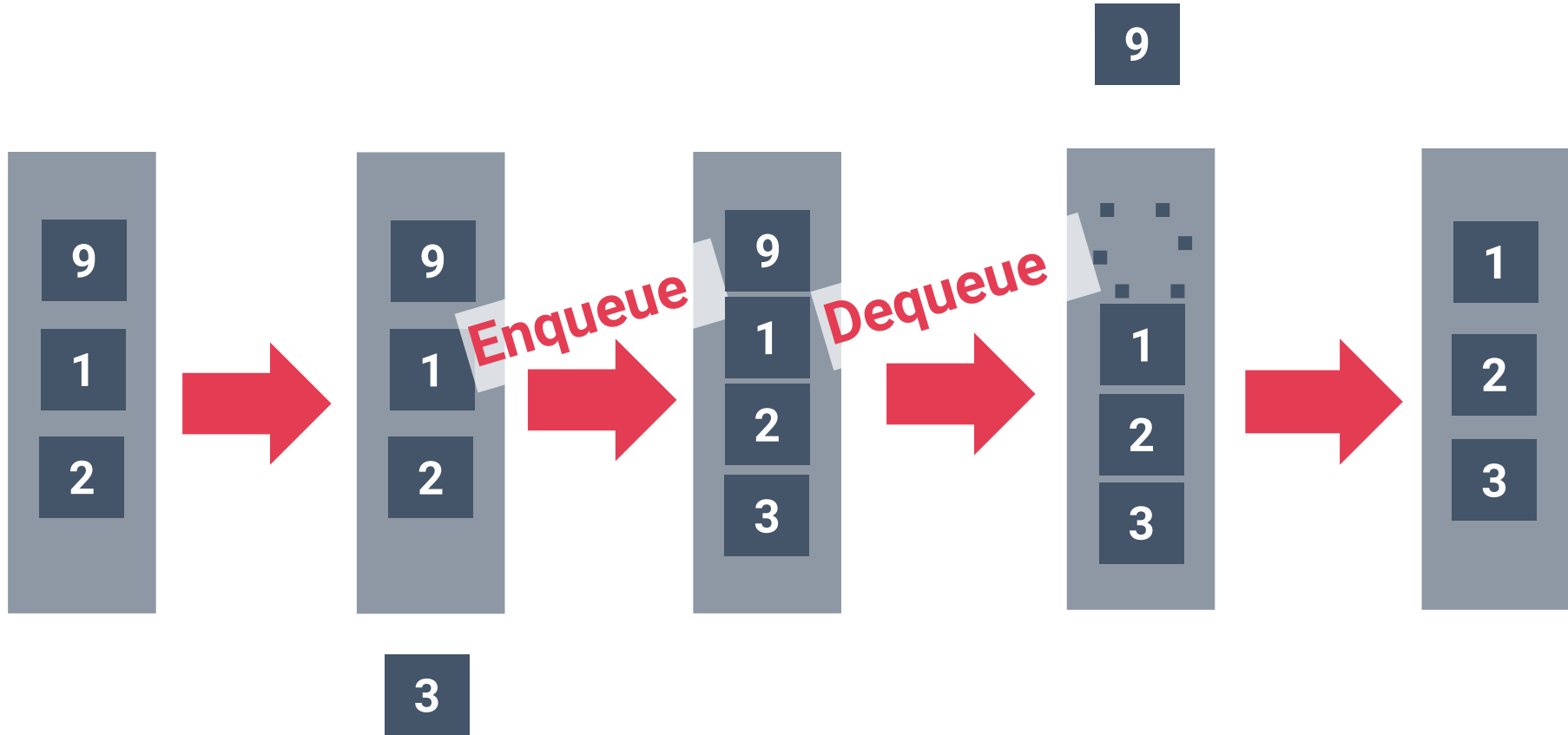
Value

Index

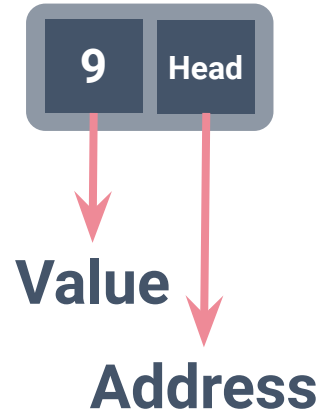
Stacks



Queues



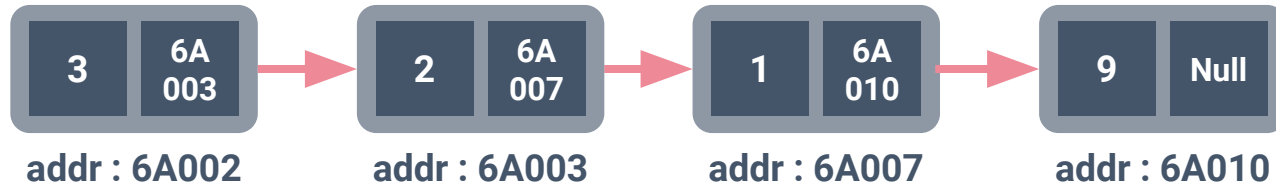
Linked Lists



Linked Lists



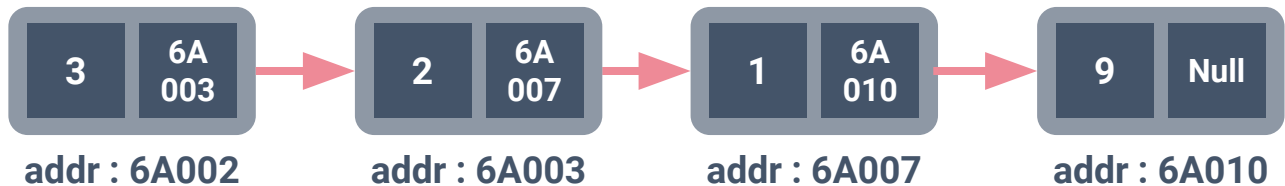
- **Linked Lists**



Linked Lists VS Arrays



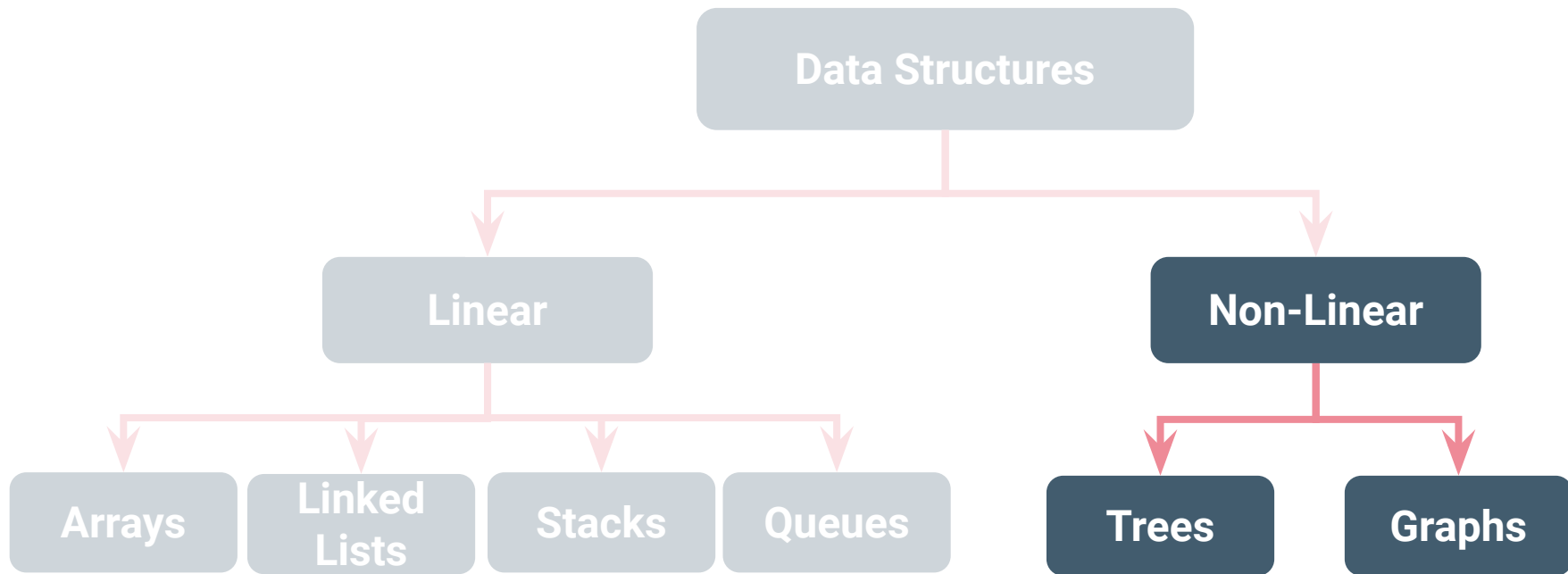
- **Linked Lists**



- **Arrays**

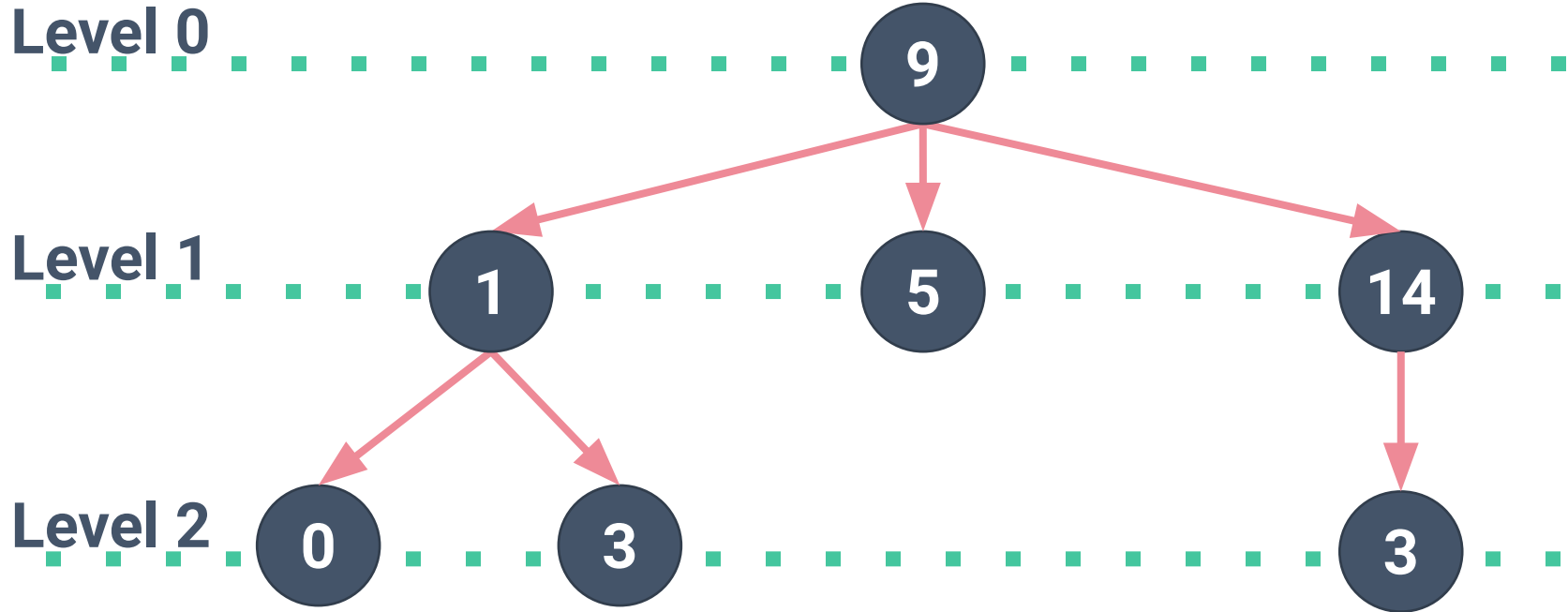


Type of Data Structure

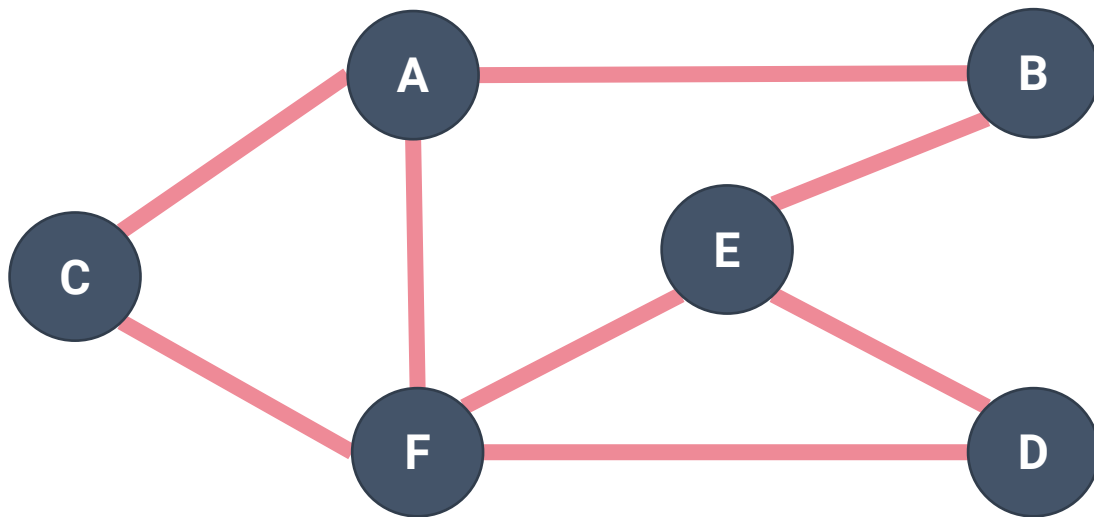


Check out for a comprehensive list of data structures at
https://en.wikipedia.org/wiki/List_of_data_structures

Trees



Graphs



Algorithm Analysis



- 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



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

Benchmark Analysis



- 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



- 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



- 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



- 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

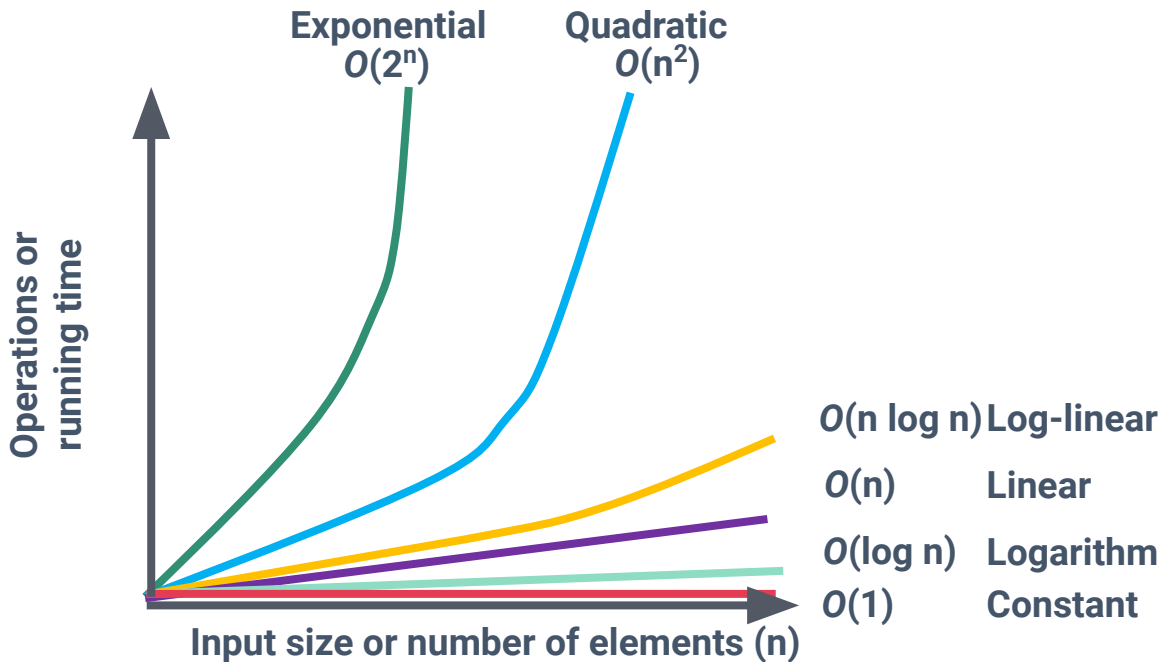


• Big-O notation (Order)

- 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.

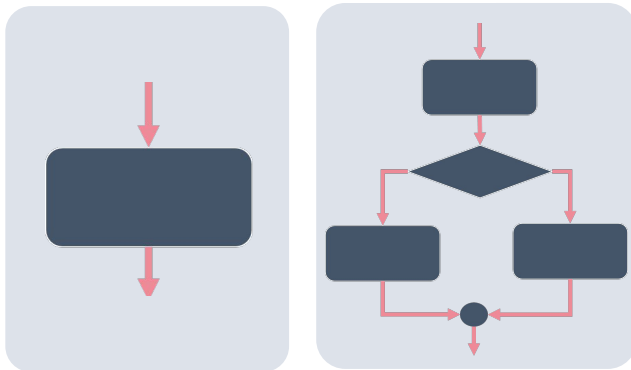


Calculating Time Complexity

Mathematic

$$f(n) = 3$$

Computer



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

Big-O

$$O(1)$$



Constant

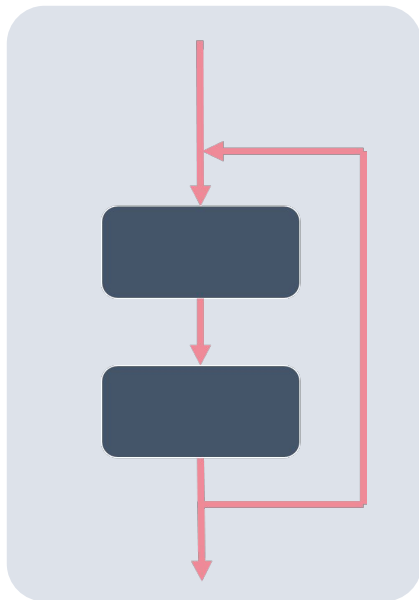
Calculating Time Complexity

Mathematic

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

Computer

Linear loop



Big-O

$$O(n)$$



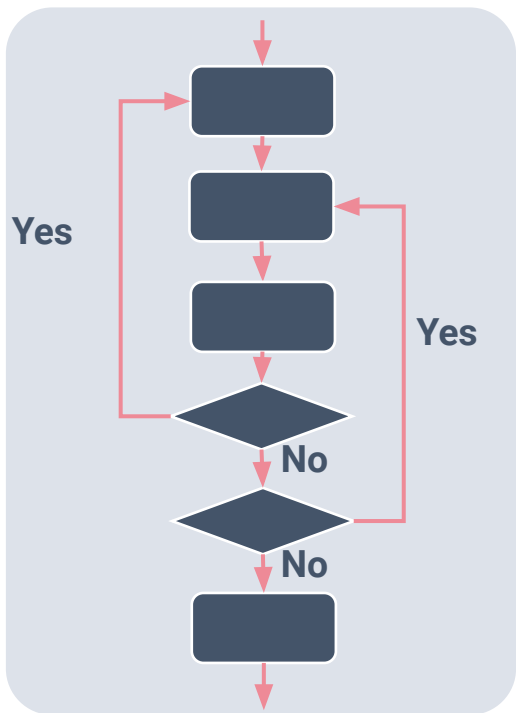
Linear

Calculating Time Complexity

Mathematic

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

Computer
Nested loop



Big-0

$$O(n^2)$$



Quadratic

Loops

Python Code

Time complexity

Linear

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



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

Linear

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



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

Nested

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



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

Loops

Python Code

Logarithmic

```

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

n=1000

→

1
2
4
8
16
32
64
128
256
512

Time complexity

→

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

Logarithmic

```

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

→

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): n  
    j = 1  
    while j < n: log n  
        do something  
        j = j*2
```



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

Loops

Python Code

Time complexity

Dependent Nested

```
for i in range (0,n): n  
    for j in range(0, i+1): (n+1)/2  
        do something
```



$$T(n) = n(n+1)/2, O(n^2)$$

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

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

For example, $n = 3$,
 $i = 0$ then $j = [0]$,
 $i = 1$ then $j = [0, 1]$,
 $i = 2$ then $j = [0, 1, 2]$

Exercise

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

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
```

Number of steps

→ 1

→ 1

→ n

→ 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))
```

Number of steps

→ **n**

→ **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
```

Number of steps

→ **n**

→ **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
```

Number of steps

→ **$n \log n$**

→ **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
```

Number of steps

→ 1

→ n

→ n

→ 1

→ $(n+1)/2$

→ 1

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

$+ n(n+1)/2$

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
```

Number of steps

→ 1

→ n

→ n

→ $(n+1)/2$

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

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
```

Number of steps

→ 1
→ n
→ 1
→ n
→ 1
→ 1

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

Complexity: $O(n)$

v3 is asymptotically better than v2 and v1

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
```

$T(n) = ?$

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
```

$T(n) = ?$

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
```

$T(n) = ?$

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
```

$T(n) = ?$

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
```

$T(n) = ?$

Complexity: $O(?)$

Exercise 2: Sequence



1) Write a flowchart that converts the **Buddhist** calendar to the **Anno Domini** calendar. At the end of the flowchart, print the Anno Domini calendar.

Best, average, or worst case?



- Example: Sequential search
- Suppose a sequence of numbers: $\langle 10, 20, 30, 40, 50 \rangle$
 - Find number 10 = 1 step = Best case
 - Find number 50 = 5 steps = Worst case
- We are interested in worst-case running time, that is, the longest running time for any input of size n .
- With any input size, it guarantees that the algorithm will never take any longer.

Example 10

Write your answer in the

1. n^2+n box

2. $3n+4n^2+n^3-12$

3. 8

4. n^4+8

5. $9n^2+3n-4n^2-6$

6. $6n+2$

7. $9+10n^2+3n-10n^2$

8. $2n+12+4n^3$

การวัดประสิทธิภาพอัลกอริทึม

$f(n)$ Asymptotic

c $\Theta(1)$

$\sum_{i=1}^k c_i n^i$ $\Theta(n^k)$

$\sum_{i=1}^n i$ $\Theta(n^2)$

$\sum_{i=1}^n i^2$ $\Theta(n^3)$

$\sum_{i=1}^n i^k$ $\Theta(n^{k+1})$

$\sum_{i=0}^n r^i$ $\Theta(r^n)$

$n!$ $\Theta(n(n/e)^n)$

$\sum_{i=1}^n 1/i$ $\Theta(\log n)$