

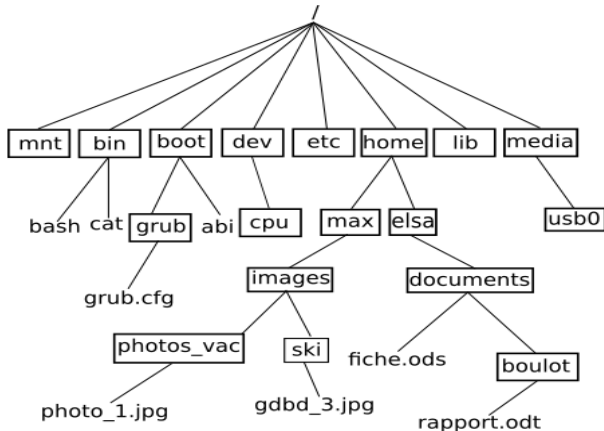
Quiz

- Define what these commands do:
 - cd
 - mkdir
 - touch
 - cp
 - mv
 - ls
- What's Git?
- What's the difference between Git and Github?
- Define the steps to update the github repo from local machine?
- What's the difference between "git push" and "git pull".

Quiz

Exercise:

- What's the absolute path of 'rapport.odt' ?
- How can I list the contents of photos_vac from boulot?
- How can I copy the contents of photos_vac to boulot from images?



Algorithmic & Python Programming

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Algorithm

Example

```
1 Function Multiply(Integer A, Integer B)
2   Integer C = 0
3   While A is greater than 0
4     C = C + B
5     A = A - 1
6   End
7   Return C
8 End
```

Algorithm

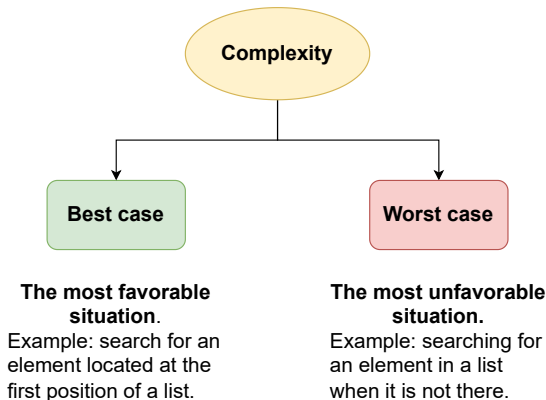
Complexity

- The calculation of the complexity of an algorithm makes it possible to measure its performance. There are two types of complexity:
 - spatial complexity: quantifies memory usage
 - time complexity: quantifies the speed of execution
- Since it is only a question of comparing algorithms, the rules of this calculation must be independent of the:
 - programming language;
 - processor;
 - compiler.
- For the sake of simplicity, we will assume that all elementary operations are at equal cost, i.e. 1 "unit" of time.
 - Example: $a = b \times 3$: 1 multiplication + 1 assignment = 2 "units"

Algorithm

Complexity: Scenarios

- Example: Sequential search for an element in an unsorted list.



Algorithm

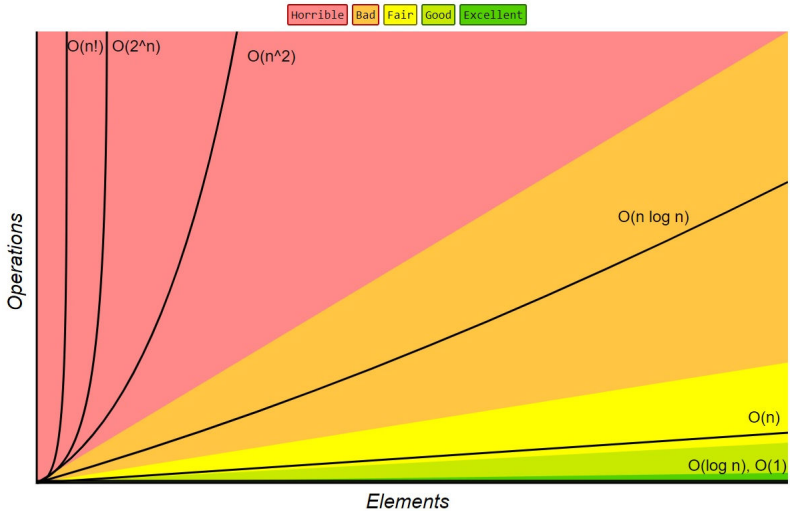
Temporal Complexity

- $\mathcal{O}(1)$: Pronounced “**order 1**” and denoting a function that runs in **constant time**
⇒ $c(n+1) = c(n) \Rightarrow \mathcal{O}(1)$
- $\mathcal{O}(n)$: Pronounced “**order n**” and denoting a function that runs in **linear time**
⇒ $c(n+1) = c(n) + 1 \Rightarrow \mathcal{O}(n)$
- $\mathcal{O}(\log n)$: Pronounced “**order log n**” and denoting a function that runs in **logarithmic time**
⇒ $c(n+1) = c(n) + \epsilon$; $(c(2n) = c(n) + 1) \Rightarrow \mathcal{O}(\log n)$
- $\mathcal{O}(n^2)$: Pronounced “**order n squared**” and denoting a function that runs in **quadratic time**
⇒ $c(n+1) = c(n) + n \Rightarrow \mathcal{O}(n^2)$
- $\mathcal{O}(2^n)$: Pronounced “**order 2 power n**” and denoting a function that runs in **exponential time**
⇒ $c(n+1) = 2 * c(n) \Rightarrow \mathcal{O}(2^n)$

$$\mathcal{O}(1) < \mathcal{O}(\log n) < \mathcal{O}(\sqrt{n}) < \mathcal{O}(n) < \mathcal{O}(n \log n) < \mathcal{O}(n^2) < \mathcal{O}(n^3) < \mathcal{O}(2^n) < \mathcal{O}(10^n) < \mathcal{O}(n!)$$

Algorithm

Temporal Complexity



Algorithm

Temporal Complexity: Example

```
1 def factorial(n):  
2     fact = 1  
3     i = 2  
4  
5     while i <= n:  
6         fact = fact * i  
7         i = i + 1  
8     return fact
```

■ Complexity

```
1 assignment: 1  
2 assignment: 1  
3 iterations: at most  $n - 1$   
4     comparison: 1  
5     multiplication + assignment: 2  
6     addition + assignment: 2
```

Algorithm

Temporal Complexity: Example $\mathcal{O}(1)$

```
1 def f1(n):  
2     print("hello")
```

■ Complexity: $T(n) = \mathcal{O}(1)$

```
1 def f2(n):  
2     s = input("enter a character")  
3     print(s)
```

■ Complexity: $T(n) = \mathcal{O}(1) + \mathcal{O}(1) = \mathcal{O}(2) = \mathcal{O}(1)$

Algorithm

Temporal Complexity: Example $\mathcal{O}(n)$

```
1 def f3(n):  
2     for i in range(n):  
3         print("hello")
```

■ Complexity: $T(n) = (\mathcal{O}(1) + \mathcal{O}(1)) \times n = \mathcal{O}(2n) = \mathcal{O}(n)$

```
1 def f4(n):  
2     s = 0.  
3     for i in range(n):  
4         s = s + i  
5     for i in range(n):  
6         s = s * i
```

■ Complexity: $T(n) = \mathcal{O}(1) + \mathcal{O}(3n) + \mathcal{O}(3n) = \mathcal{O}(6n + 1) = \mathcal{O}(n)$

Algorithm

Temporal Complexity: Example $\mathcal{O}(n^2)$

```
1 def f5(n):  
2     for i in range(n):  
3         for j in range(n):  
4             s = s + i*j
```

■ Complexity: $T(n) = \mathcal{O}(5n^2) = \mathcal{O}(n^2)$

Algorithm

Temporal Complexity: Example $\mathcal{O}(\log n)$

```
1 n = 300
2 count = 0
3 while n != 0:
4     n //= 2
5     count += 1
6 print("repetition count is:", count)
```

```
1 repetition count is: 9
```

- Number of repetition is: $1 + \log_2(300) = 9.2 \approx 9$
- Complexity: $T(n) = \mathcal{O}(5 \times (1 + \log_2 n)) = \mathcal{O}(\log_2 n)$

Algorithm

Temporal Complexity: Example $\mathcal{O}(n \log n)$

```
1 m = n = 300
2 count = 0
3
4 while m != 0:
5     while n != 0:
6         n //= 4
7         count += 1
8     m -= 1
9 print("repetition count is:", count)
```

```
1 repetition count is: 5
```

- Number of repetition is: $(1 + \log_4(300)) = 4.1 \approx 5$
- Complexity: $T(n) = \mathcal{O}(8n \times (1 + \log_4 n)) = \mathcal{O}(n \log_4 n)$

Algorithm

Temporal Complexity: Example $\mathcal{O}(2^n)$

```
1 def fibonacci(n):
2     if(n <= 0):
3         return n
4     else:
5         return (fibonacci(n-1) + fibonacci(n-2))
6 n = int(input("Entrez le nombre de termes:"))
7 print("Suite de Fibonacci en utilisant la recursion :")
8
9 for i in range(n):
10     print(fibonacci(i))
```

- if $n = 1$: 3 calls = $2^1 + 1$
- if $n = 2$: 5 calls = $2^2 + 1$
- if $n = 3$: 9 calls = $2^3 + 1$
- if $n = 4$: 15 calls = $2^4 - 1$
- if $n = 5$: 25 calls = $2^5 - 7$
- General case:
 - Complexity: $T(n) = \mathcal{O}(2^n + \text{const}) = \mathcal{O}(2^n)$