







# **Complexity**

### **Algorithms we know**

- Linear Search, Binary Search
- Selection Sort, (will see Merge Sort)
- **Algorithms** can be **ranked** in terms of **time** (or space) **efficiency**
- **n** is # elements we have.
- $N$  is # operations our algorithm does.
- Rate algorithm by a **reference function** which closely represents how N grows as n gets larger.





# **This lesson**

- Complexity and Big O Notation
- Analysis of brief algorithms
- Analysis of Linear Search
- Analysis of Binary Search
- Analysis of Selection Sort
- Analysis of Merge Sort



Exp



## **How do we calculate time complexity?**

- **Count** the number of times a **critical operation** is executed
	- Usually seen in a loop
- **Disregard** "**constants**"
	- Usually seen as unindented lines, and independent of input size
- **Disregard** "**lower exponent terms**" (e.g., for **3 n2 + 15n +35**; ignore the **+15n**, ignore the **+35** ).

Let's see some examples!



## **Calculating Time Complexity - Example 1**

 $1 \times = \emptyset$ 2  $v = 10$  $3 \times += 1$ 4 for i in range(n): 5  $x + = y$ 6  $v = 1000$ 

- Count the number of times a critical operation is executed
- Disregard "constants"
- **Disregard "lower exponent terms"**
- Critical operations depending on n?
	- addition (lines 5&6)
- What are the constants?
	- $\cdot$  lines 1-3
- How many addition/assignments that matters are executed?
	- 2<sup>\*</sup>n (lines 5&6 repeated n times)
- What is the time complexity?
	- $\bullet$  O(n)



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## **Calculating Time Complexity - Example 2**

```
1 count = \theta2 for i in range(n):
3 count = count + 10
4 for j in range(n):
5 count = count + i
```
- Count the number of times a critical operation is executed
- **Disregard "constants"**
- **Disregard "lower exponent terms"**
- Critical operations depending on n?
	- addition (lines 3, 5)
- What are the constants?
	- Line 1
- How many additions that matter are executed?
	- $n + n = 2n$  (line 3 repeated n times, so is line 5):
- What is the time complexity?
	- $\bullet$  O(n)



## **Calculating Time Complexity - Example 3**

```
1 count = \theta2 for i in range(n):
3 for j in range(n):
4 count = count + 10
```
- Count the number of times a critical operation is executed
- **Disregard "constants"**
- **Disregard "lower exponent terms"**
- Critical operations depending on n?
	- addition (line 4)
- What are the constants?
	- Line 1
- How many additions that matters are executed?
	- $n * n = n^2$  (line 4 repeated n times in j loop, which repeated n times in i loop)
- What is the time complexity?
	- $\bullet$  O(n<sup>2</sup>)



## **Calculating Time Complexity - Example 4**

```
1 count = \theta2 for i in range(n):
3 for j in range(n):
4 count = count + 10
5 for j in range(n):
6 count += 2
```
- Count the number of times a critical operation is executed
- Disregard "constants"
- **Disregard "lower exponent terms"**
- Critical operations depending on n?
	- addition (lines 4&6)
- What are the constants?
	- Line 1
- How many addition/assignments that matters are executed?
	- $(n + n) * n = 2n^2$  (line 4 repeated n times in j loop, so is line 6, both loops repeated n times in i loop)
- What is the time complexity?
	- $O(n^2)$  (can omit the coefficient if it is a number)



### **Best case, worst case, average case**

- When the running time depends on the data (and not a variable already in the program), we can calculate best case, worst case, and average case scenarios
- For example, suppose we are performing a Linear Search…
	- **Best case scenario** happens when the first element we check is what we are looking for (no need to go through the list)
	- **Worse case scenario** happens when the last element we check is what we are looking for, or it doesn't exist (have to go through the list to know)
	- **Average case scenario** happens when the element we look for has an equal chance to be anywhere in the list

## **Linear search complexity**

```
# Input: List of numbers, number to search for
# Output: The first index where number can be found, -1 if not in list
def linear search index (input list, item):
 for i in range(len(input_list)):
   if input_list[i] == item:
     return i
 return -1
```
Best case : Returned position **i** is **0 Worst case**: Two possible situations Last item: Returned position **i** is **n-1** Not found: Returned position  $\mathbf{i} = -\mathbf{1}$ **O(n) O(1)**

**0**

**n-1**

# **Let's analyze this algorithm**



- Count the number of times a critical operation is executed
- Disregard "constants"
- Disregard "lower exponent terms"
- Critical operations depending on n? ○ addition (lines 4&5)
- What are the constants?  $\circ$  Lines 1&2
- How many addition/assignments that matters are executed?
	- 2\*k (lines 4&5 repeated k times)
- What is the time complexity?
	- $\circ$  O(k)  $\leftarrow$  not the answer yet as it should be a function of n

# **Let's analyze this algorithm**



- Count the number of times a critical operation is executed
- Disregard "constants"
- Disregard "lower exponent terms"
- **Observation**: instead of decreasing 1 in each iteration, **i decreases by half**
- Then the question becomes: "How many times can the while-loop **divide n by 2** until it becomes 1 (as it ends in the next iteration)?"
- Suppose **n** is a power of **2** (e.g., 210) We can do that because if not, n is going to be between two such numbers (e.g.,  $2^6$  < 100 <  $2^7$ )
- Let  $\mathsf{n}$  =  $2^k$ . Then, what is k?

# **The concept of logarithm**

If the number of elements is **n**, and **n = 2k** And we would like to know what **k** is, how can we solve for **k**? We can use logarithm:

 $\log_2 n = k$ 

- So, if n is 2<sup>10</sup>, then k is 10  $\rightarrow$  while-loop needs to divide 10 times; and if n is  $2<sup>k</sup>$ , then while-loop needs to divide k times
- Therefore, our algorithm has a **O(logn)** time complexity

### **Intuition of an O(log n)**  100 $\frac{n! 2^n n^2}{\prod_{i=1}^{n} n^2}$  $n \log_2 n$ **algorithm** 90

In each stage the algorithm processes half of the previous stage. Which algorithms have we seen that process half of the previous stage each time?



## **Binary Search**

## **analysis**

One path from the top to the bottom is a full search for a value.

The height of this tree is equal to the number of comparisons needed to find the item in the worst case.



The height of the tree is the answer to the following question: **How many times do we divide the problem of size n by 2**  until we get down to a problem size of 1?

Credit:<https://stackoverflow.com/questions/2307283/what-does-olog-n-mean-exactly/13093274>

```
# Input: An unsorted list of numbers
# Output: Returns a sorted list of numbers
          (Input list is unchanged)
#
def selection sort(data original):
    # Make a copy so we don't change the original
    data = data original[:]# For each spot in the list, find the next smallest number
    # in the remaining sublist of our numbers
    for i in range(len(data)):
        # Start by assuming smallest element is first in sublist
        min number = data[i]min idx = i# Look through rest of sub-list for smallest element
        for j in range(i + 1, len(data)):
            if data[j] \langle min number:
                min number = data[j]min idx = j# Swap the current element with the next smallest element
        temp = data[i]data[i] = data/mindata/min idx = temp
```
## **Selection Sort**

### A reminder from last time!

- test =  $[5,3,6,2,1]$ 28
- print(selection sort(test)) 29
- $print(test)$ 30

1

2

3

 $\overline{4}$ 

5

6 7 8

9

 $10$ 

 $11$ 

 $12$ 

13  $14$ 15

16

17

18

19

20

21

 $22$ 

23

 $24$ 25

26



## **Complexity of Selection Sort**

**Selection Sort** looks for the smallest element multiple times, by going through n elements, then n-1 elements, then n-2 elements.

The total number of operations (comparisons) is therefore:

$$
= n + (n-1) + (n-2) + ... + 3 + 2 + 1
$$

 $= n (n + 1) / 2$ 

$$
= \boxed{n^2 / 2} + n / 2
$$

Selection sort is **quadratic, O(n2).**  This is true for both the **best** and **worst case (why?)**

### **Now we have analyzed 3 algorithms!**

We used **Big O** Notation to describe these algorithms' **worst case** runtime:

- **O(n)** Linear search
- **O(logn)** Binary search
	- **O(n<sup>2</sup>)** Selection sort



<http://www.cs.sfu.ca/CourseCentral/120/ggbaker/guide/parts/guide06>



## **Is sorting worth it?**

Binary search **requires** the data to be **sorted**. Sorting can be **expensive**, e.g. **O(n2)**

Even if **binary search** is **O(logn)**, wouldn't the exponential cost of sorting make this approach worse than **linear search O(n)**?

Think: In what cases would it be worth it to sort, then perform binary search?

<http://interactivepython.org/courselib/static/pythonds/SortSearch/TheBinarySearch.html>

input size, e.g. list to search/sort



## **What happens when n gets larger?**





## **Introducing Merge Sort**

• **Mergesort** is much faster than Selection Sort (along with shellsort, quicksort, etc.)

https://visualgo.net/bn/sorting

### **How do you merge 2 sorted lists?**



result

Start from the beginning of each list. Pick the smaller item and append it to the result list, repeat until both lists are empty

### **Merge sort**

- Split the list until there is one element
- Progressively recombine neighbouring sorted lists using the merge function we defined earlier



### **Merge sort**

### **Mergesort** can be implemented as a recursive algorithm:

- It has a base case: stop when there is just one item to sort
- It has a recursive case: give itself a sublist to sort
- It changes the input towards the base case: the sublist is a smaller list



## **Mergesort – Pseudocode**

```
The function merge() is a non-
                                                                  recursive helper function that creates 
                                                                  a new sorted list by merging the two 
                                                                        sorted lists (see pg. 6)
                                                                  is recursive as it 
                                                                  calls itself with a 
                                                                    smaller list
1 mergeSort(alist):
2 if (alist has 2 or more elements): 
3 sortedLeft = mergeSort(left half of alist)
4 sortedRight = mergeSort(right half of alist)
5 result = merge(sortedLeft, sortedRight)
6 else: 
7 result = alist # list is already sorted, 1 element only
8 return result
```
**mergeSort**() itself

One way to think of it is instead of tracing how the recursion unfolds, focus on the current step: **It recursively calls itself with 2 halves (lines 3&4), and "magically" gets the halves back sorted. The merge them into one sorted list (line 5)**

## **Complexity of mergesort?**

- Height of the tree (just as in binary search) ⇒ **log n**
- Merge operation for all the elements ⇒ **n** operations



## **Complexity of mergesort?**

**O(nlogn)** 

### (n times log n)

*Intuitively, considering various operations:* 

- Height of the tree (just as in binary search) ⇒ **log n**
- Merge operation for all the elements  $\Rightarrow$  **n** operations

**Note: Extra space is needed to create the merged lists** at each level. This may be problematic for large n.

> Other sorting algorithms do all the operations in place, e.g., swapping with only 1 temp variable needed.



# **Review**

Give the worst case time complexity for each of the algorithms below.

- Linear search
- **Binary search**
- Selection sort
- Merge sort

Options: O(n!), O(1), O(n2),O(n), O(nlogn), O(logn), O(n3)

# **Review**

Assume that a problem can be solved with two different algorithms, and you need to decide which algorithm to implement based on their time complexity.

Their time complexities are **O(n)** and **O(nlogn)**.

Which algorithm would you choose, if you had a very large dataset?



