# PG4200: Algorithms And Data Structures

Lesson 03: Runtime Analysis and Sorting

Prof. Andrea Arcuri

#### How Long?



- You want fast algorithms
- You could just run some "experiments", and check how long your algorithm takes
- But what if algorithm will need to be run on a larger problem than I used in the experiments?
- If the problem is twice as big, will my algorithm take just twice as long???

```
public static int sum(int[] array) {
   int sum = 0;
   for(int i=0; i<array.length; i++) {
       sum += array[i];
   }
   return sum;
}</pre>
```

- "Cost" can be measured in number of executed statements
- Given size of array N, the loop will be taken N times
- There is some constant cost independent of N, eg creation of "int sum" variable
- If N doubles, would expect function will be roughly twice as slow

#### instructions(N) = 3N + 4

#### instructions(N=0)=4

```
    int sum = 0;
    int i=0;
    i<array.length;</li>
    return sum;
```

- Number of instructions depends on size N of the array, plus some constant cost
- Can be represented with a function, eg f(N)=3N+4
- For large N, constants are not important

#### instructions(N=3)=13

```
1. int sum = 0;
   2. int i=0;
   3. i<array.length;</pre>
      sum += array[i];
4. sum += array[1]
5. i++
6. i<array.length;</pre>
sum += array[i];
  -10. sum += array[i];
   12. i<array.length;</pre>
   13. return sum;
```

```
On my machine, repeated 100 times:
public static int pairs(int[] array) {
                                                                seconds=0.005
                                                       N=100
    int pairs = 0;
                                                               seconds=0.005
                                                       N=2.00
                                                       N=400 seconds=0.012
    for(int i=0; i<array.length; i++) {</pre>
                                                       N=800
                                                               seconds=0.072
         for(int j=0; j<array.length; j++) {</pre>
                                                       N=1600 seconds=0.211
             if(i!=j && array[i] == array[j]){
                                                       N=3200 seconds=0.754
                  pairs++;
                                                       N=6400 seconds=2.829
                                                       N=12800 \text{ seconds}=11.48
    return pairs;
```

- Two nested loops
- Inner loop executed once per each element in array
- So,  $N * N = N^2$
- Twice as big is now 2 \* 2 = 4 times as slow!!! (roughly)

#### Scalability

- When analyzing algorithms, we will not look at the low level optimization details
- N as representation of the problem size (eg, length of array or number of elements in a container)
- How does the algorithm scale for larger sizes???
- Example: if my website works fine with a load of 100 users, what will happen with 2,000??? Will I just need 20 times the resources?

## Wheat/Rice and Chessboard Problem



- 1 rice grain on first square
- Double at each square
- How many grains on the board?
- 18,446,744,073,709,551,615
- ie, 18 Quintillions

## Analysis of Algorithms

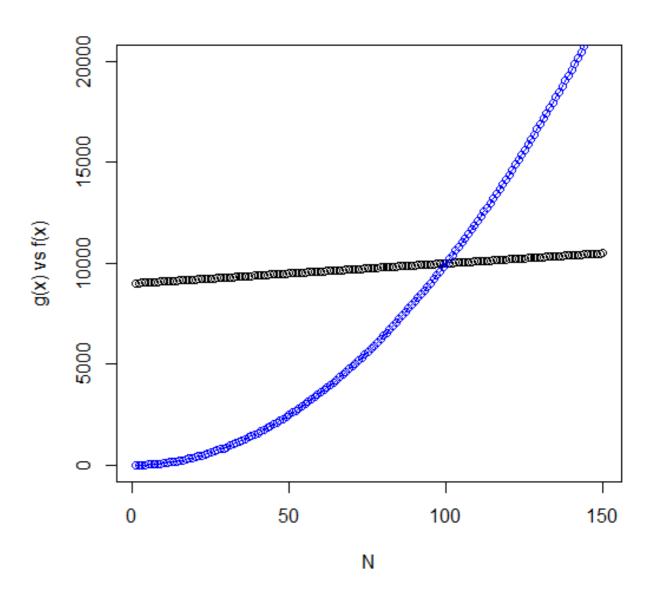
- Mathematically define the cost as a function of the input size
- Precise functions can be impractical, so we need approximations
- Usually, we are interested in upper and lower bounds

## Example

- $f(n) = a N^2 + b N + c$
- Given an algorithm whose performance is described by the polynomial f(n), finding the actual values for a, b, c might be too difficult
- However, can we say something about the scalability?
- YES!!! Regardless of a = 5 or a = 400, still doubling *N* would result in increase of at least 4 times (roughly...)

#### Which Is Better?

- $f(n) = n^2$
- g(n) = 10 n + 9000
- For small values f(n) is better, but it become worse from n > 100
- We will look at *large* n, so for us g(n) is better



## Large N???

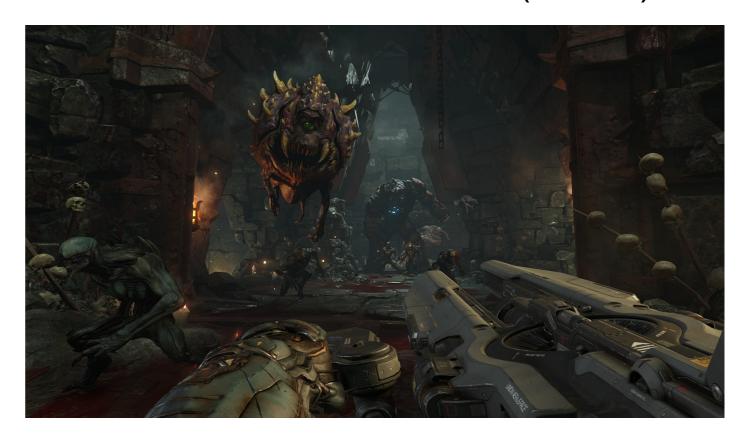
- How do we define large?
  - 10? 50? 10000000000000000???
- We can't really say... however, things grow so fast... what we think is *large* today, is likely going to be considered *tiny* in few years...
- Today I know how fast my algorithms are, because I run them. But I want to know how they will scale to the larger problem instances of tomorrow.
  - Eg, when my apps get more users

## FPS... large increase in number of polygons to render...



Doom (1993)

Doom (2016)



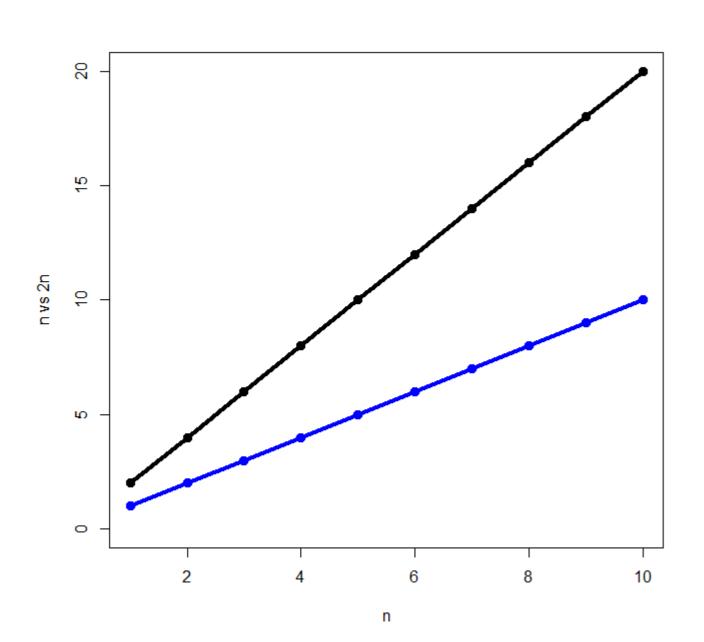
#### Scalability

- f(n) = 5n + 100
  - If I am interested in scalability, the constants 5 and 100 are *irrelevant*
- $g(n) = 2n^2 + 10n + 7$ 
  - The constants 2, 10 and 7 are irrelevant. But what about the n compared with  $n^2$ ??? It is smaller, but maybe still important?

#### Big O Upper Bound

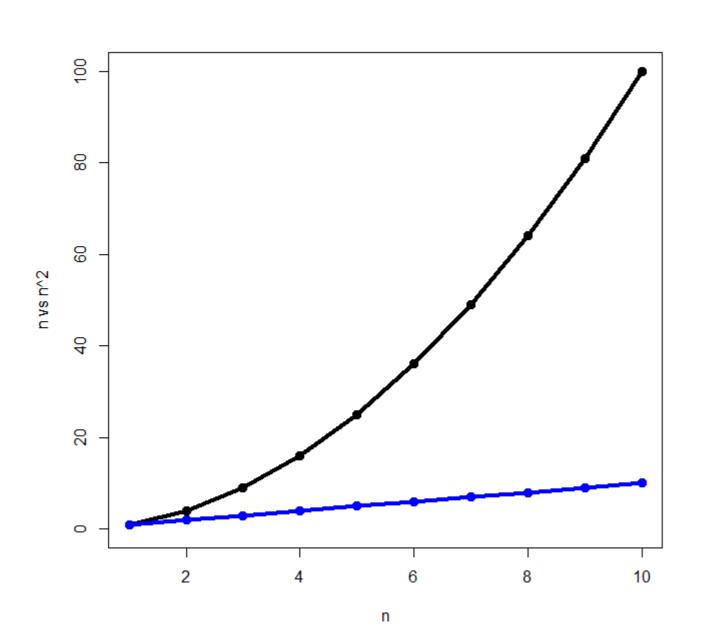
- f(n) = O(g(n))
- If there exists positive constants c and n', such that  $0 \le f(n) \le c * g(n)$  for all  $n \ge n'$
- In other words, c \* g(n) is an **upper bound** for f(n) for large values of n
- Useful to consider worst case scenarios

$$n = O(n)$$



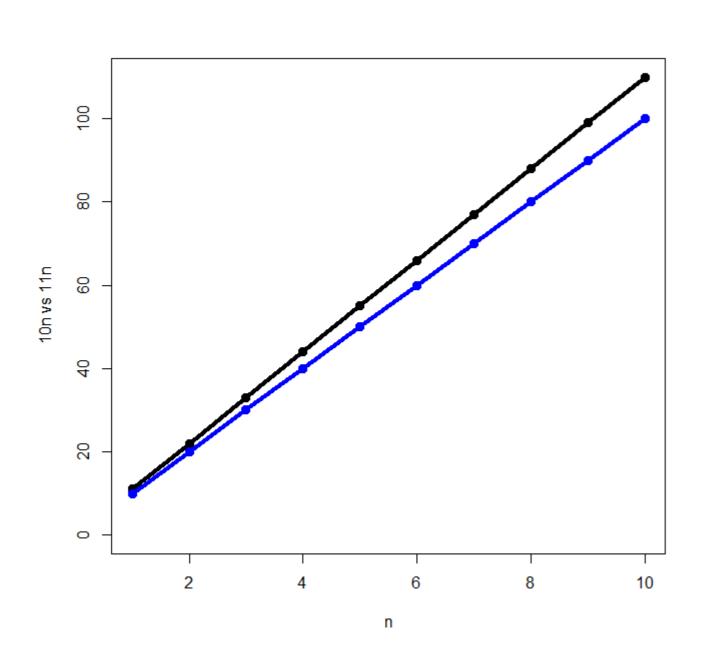
- g(n) = n
- Examples: c = 2, n' = 1
- n < 2n for n > = 1

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



- $g(n) = n^2$
- Examples: c = 1, n' = 2
- $n < n^2$  for n > = 2

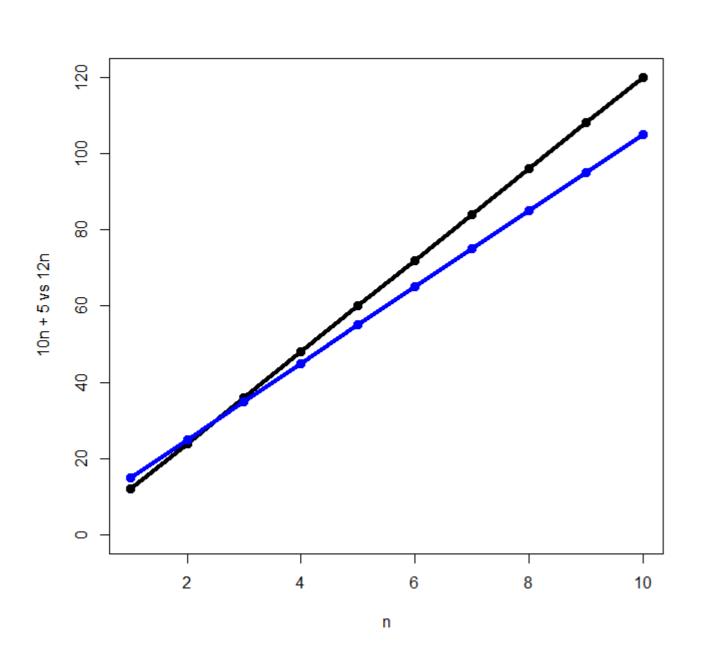
#### 10n = O(n)



• 
$$g(n) = n$$

- Examples: c = 11, n' = 1
- 10n < 11n for n >= 1

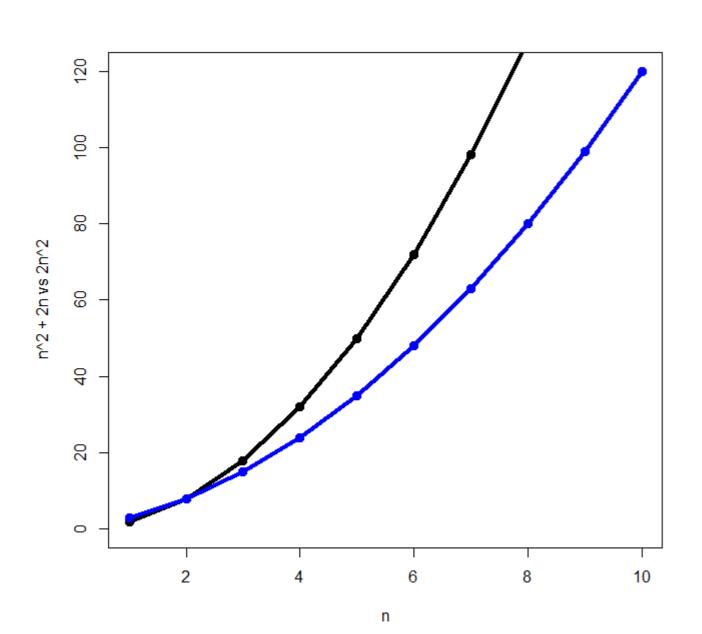
#### 10n + 5 = O(n)



• 
$$g(n) = n$$

- Examples: c = 12, n' = 3
- 10n + 5 < 12n for n > = 3
- Eg: n=3 -> f(n)=35, g(n)=36
- Note: for n<=2, f(n) is actually larger

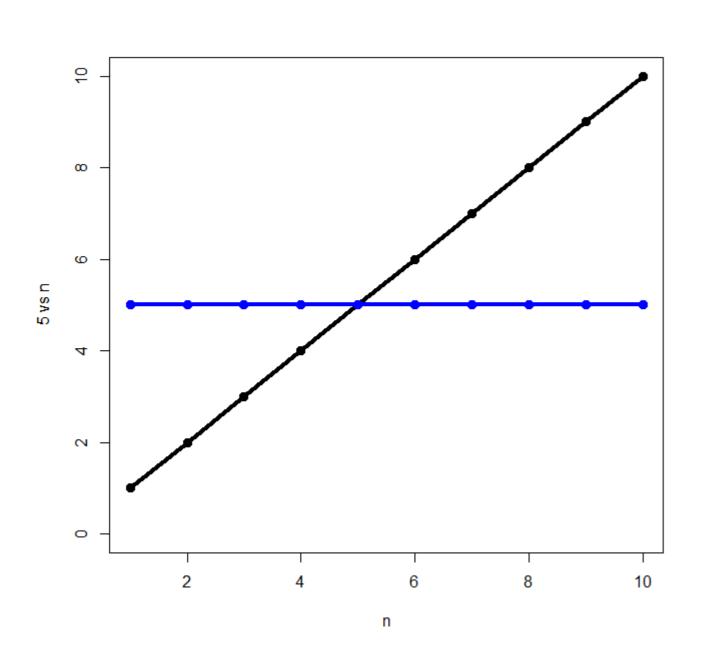
#### $n^2 + 2n = O(n^2)$



• 
$$g(n) = n^2$$

- Examples: c = 2, n' = 3
- $n^2 + 2n < 2n^2$  for n >= 3
- Eg: n=3 -> f(n)=15, g(n)=18

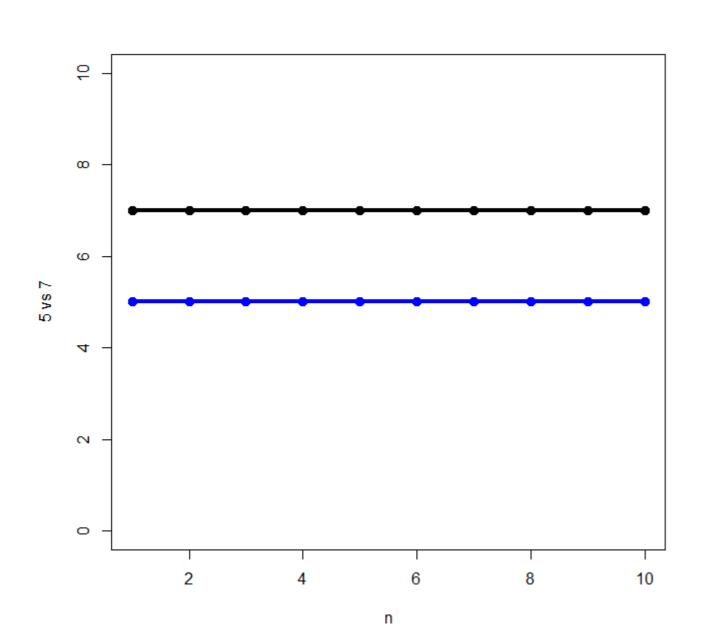
$$5 = O(n)$$



• 
$$g(n) = n$$

- Examples: c = 1, n' = 6
- 5 < n for n >= 6

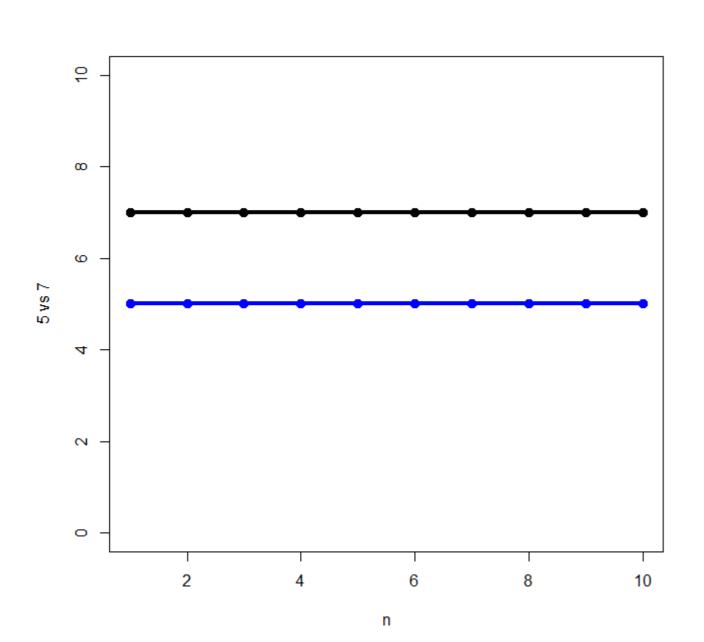
$$5 = O(7)$$



• 
$$g(n) = 7$$

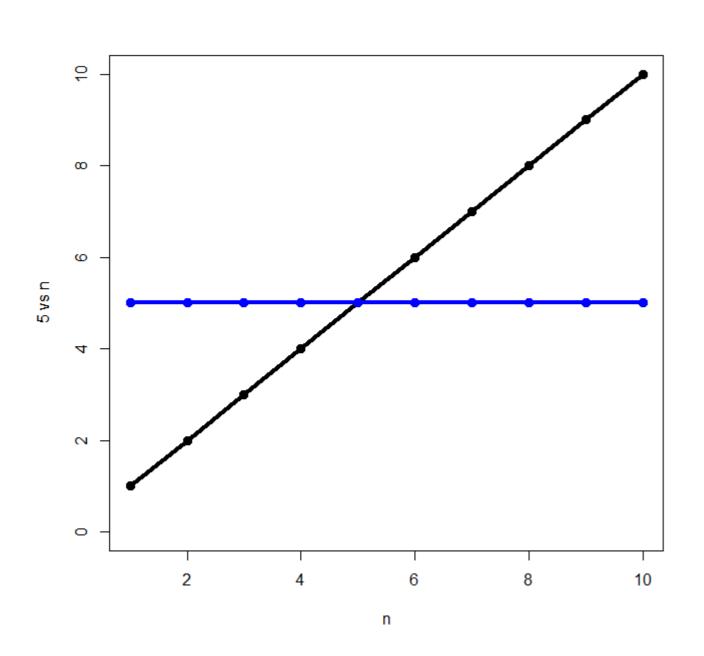
- Examples: c = 1, n' = 1
- 5 < 7 for regardless of n

$$5 = O(1)$$



- g(n) = 1
- Examples: c = 7, n' = 1
- 5 < 7 for regardless of n

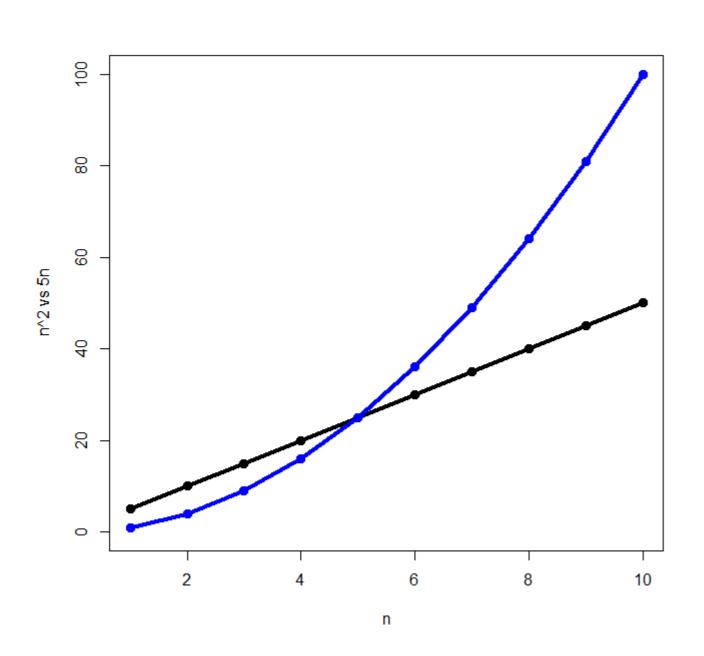
#### $n \neq O(1)$



• 
$$g(n) = 1$$

Whatever c I use (eg 5),
 f(n)<c will not hold for n'>c, eg n'=c+1

## $n^2 \neq O(n)$



• 
$$g(n) = n$$

Whatever c I use (eg 5),
 f(n)<cn will not hold for n'>c, eg n'=c+1

## Big O Examples

• 
$$n = O(n)$$

• 
$$n = O(n^2)$$

• 
$$10n = O(n)$$

• 
$$10n + 5 = O(n)$$

• 
$$n^2 + 2n = O(n^2)$$

• 
$$5 = O(n)$$

• 
$$5 = O(7)$$

• 
$$5 = 0(1)$$

• 
$$n \neq 0(1)$$

• 
$$n^2 \neq O(n)$$

#### Big O Rules of Thumb

- When you have a polynomial, for upper bound just look at the highest exponent
- $an^3 + bn^2 + cn + d = O(n^3)$
- This means that, when analyzing an algorithm, you can ignore the parts with less impact
- When representing constants independent from the problem size, just use 1 by convention, eg O(1)

#### Notation

- $O(g(n)) = \{ f(n) : \text{ there exists positive constants } c$ and n', such that  $0 \le f(n) \le c * g(n)$  for all  $n \ge n' \}$
- O(g(n)) is actually a set of functions
- f(n) = O(g(n)) is not fully correct as notation, as we use it to represent the fact that f(n) is one member of the set O(g(n))
- $f(n) \in O(g(n))$  would be more precise, but often for simplicity you will see "=" instead of " $\in$ "

#### Big \O Lower Bound

- $f(n) = \Omega(g(n))$
- If there exists positive constants c and n', such that  $0 \le c * g(n) \le f(n)$  for all  $n \ge n'$
- In other words, g(n) is a *lower bound*
- Useful to consider how expensive algorithm is even in the best possible scenario
- $\Omega(1)$  is a trivial lower bound valid for all functions

#### Big @ Tight Bound

- $f(n) = \Theta(g(n))$
- If there exists positive constants c, d and n', such that  $0 \le c * g(n) \le f(n) \le d * g(n)$  for all  $n \ge n'$
- In other words, this happens when the lower and upper bounds are asymptotically the same (and just differ by the constant)

```
public static int sum(int[] array) {
   int sum = 0;
   for(int i=0; i<array.length; i++) {
      sum += array[i];
   }
   return sum;
}</pre>
```

- In this case, the actual cost in number of instructions is f(n) = 3n + 4
- Asymptotically, we can say that  $3n+4 = \Theta(n)$
- As the number of instructions does not depend on the content of the array, the best case and worst case for the runtime are the same

#### Order Of Growth Classification

- 1: constant (best you can have)
- log(N): logarithmic (very, very efficient)
- N: linear (OK for most cases)
- N log(N): **linearithmic** (OK for most cases)
- N<sup>2</sup>: quadratic (bearable, but things start to get expensive)
- N<sup>3</sup>: **cubic** (becoming painful)
- 2<sup>N</sup>: **exponential** (*completely hopeless*, time to cry in a corner)

#### Which Scales Best?

• 
$$f(n) = O(n)$$

• 
$$g(n) = \Omega(n)$$

• 
$$t(n) = \Omega(n \log(n))$$

• 
$$k(n) = O(n^2)$$

• 
$$Z(n) = \Theta(n)$$

The **only** thing that I can say for sure is that f(n) is better than t(n). Why???

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

#### In Practice

- Proving tight bounds is often infeasible
- Usually, from practical standpoint, the worst case scenario is what matters, so most discussions are about O(g(n))
- Often, lower bound is not so interesting, as in happy-day scenario you get  $\Omega(1)$

#### A Big Mistake

- BIG MISTAKE: assuming that an upper bound is tight, eg claiming f(n) = O(n) is necessarily better than  $g(n) = O(n^2)$ 
  - Although you might still want to prefer f(n) if you do not have any other information
- Even if a lower upper bound O exists, it might be too difficult to formally prove it, so  $O(n^2)$  might just be the best approximation we currently have
- However, it is also important to consider that worst case scenario is different from the average one, but proving averages is much more difficult

- Note the "int j=i". What can we say about that function?
- Without digging into the math, we can say that, even in best case, first loop is taken at least once, so  $\Omega(n)$
- In worst case, not worse than assuming "int j=0", so  $O(n^2)$ 
  - In other words, we can mentally consider a more expensive algorithm which does more iterations, but that is easier then to analyze
- Is the true complexity closer to the lower or to the upper bound? Maybe Θ(n log n)???

## Let's Dig Into the Math...

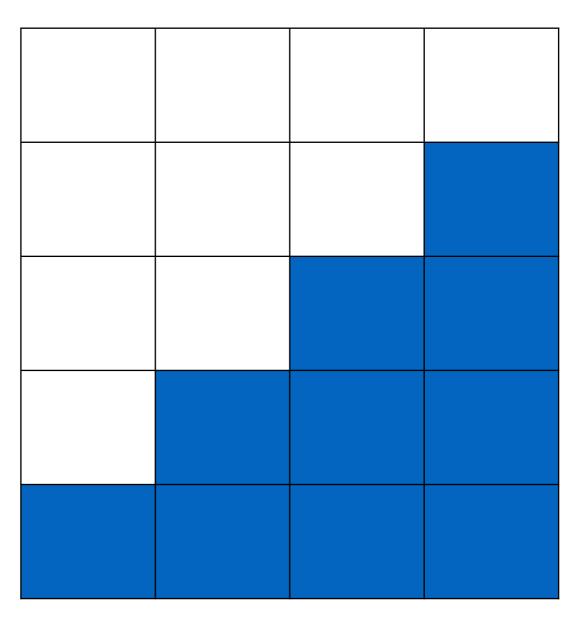
```
public static void doSomething(int[] array) {
    for(int i=0; i<array.length; i++) {
        for(int j=i; j<array.length; j++) {
            //... something</pre>
```

- Outer loop is taken N times
- Inner loop is shorter by 1 at each iteration

• 
$$N + (N - 1) + (N - 2) + ... + 1 = \sum_{i=0}^{N} i = \frac{1}{2}N(N + 1) = \frac{1}{2}(N^2 + N) = \Theta(N^2)$$

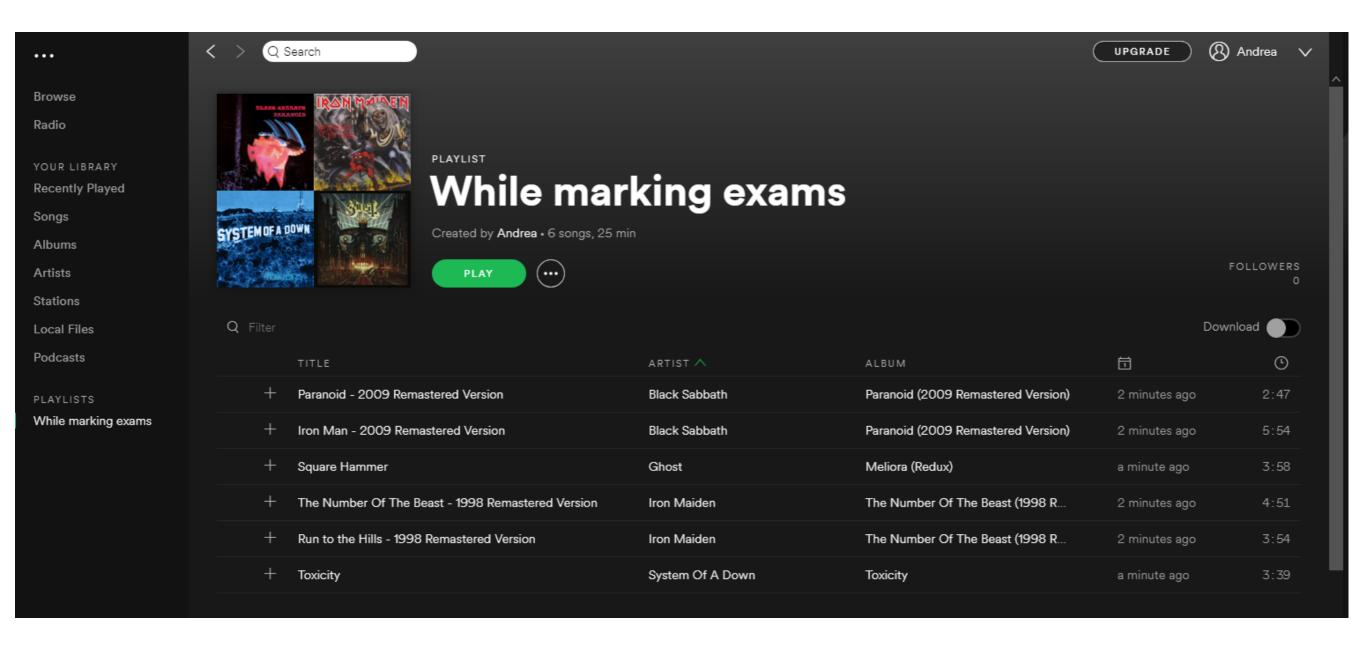
$$\sum_{i=0}^{N} i = \frac{1}{2}N(N+1)$$

- Think about a rectangle with sides N and N+1
- Its area is N \* (N + 1)
- But we are interested only in the colored area, so divide by 2
- 1+2+3+4=4\*5/2=10

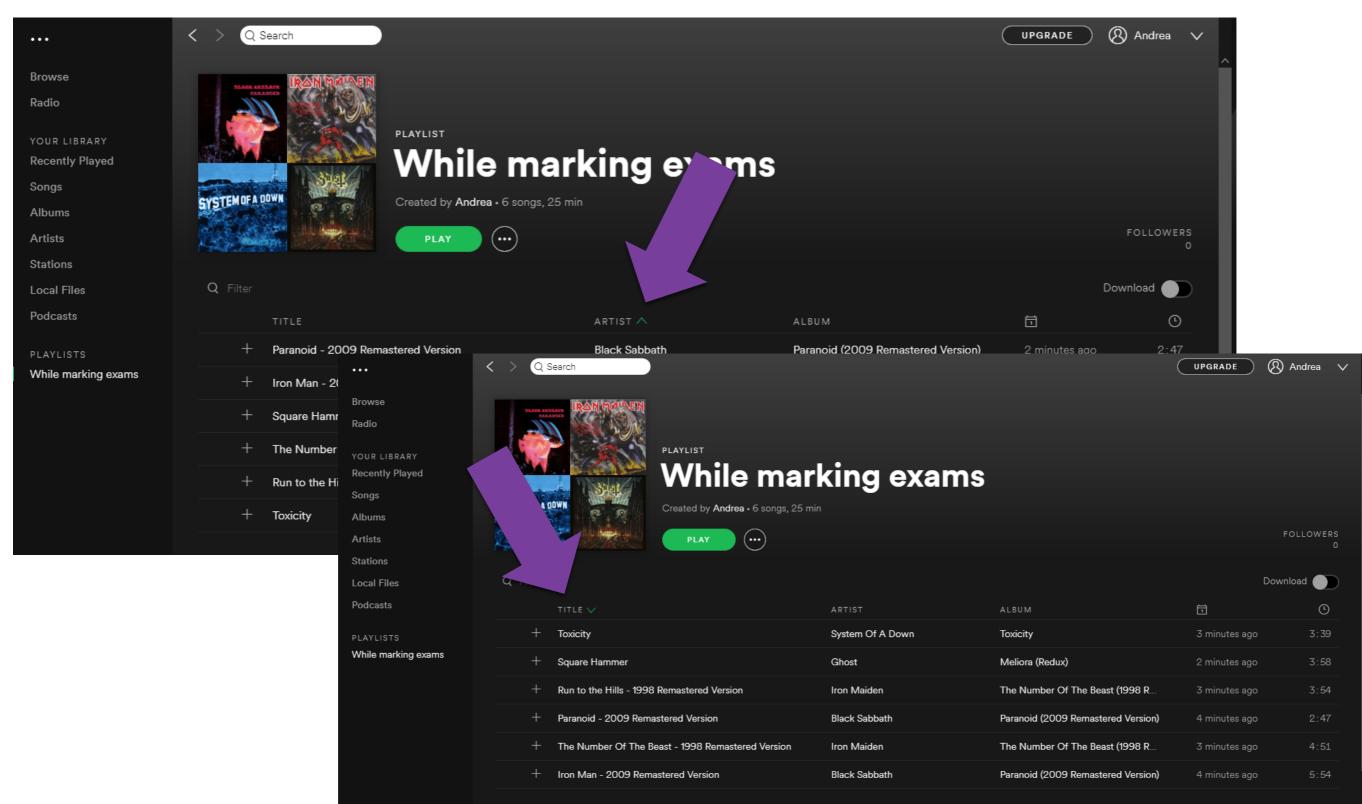


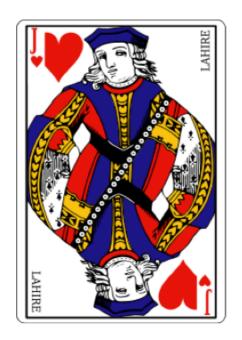
## Sorting

## Consider a Playlist



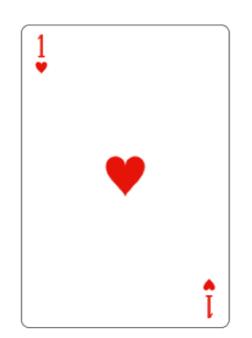
### Sort by Title or Artist, Ascending or Descending

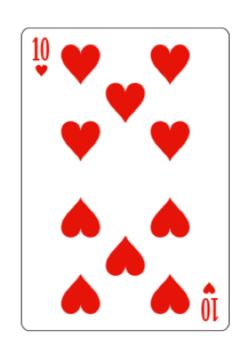




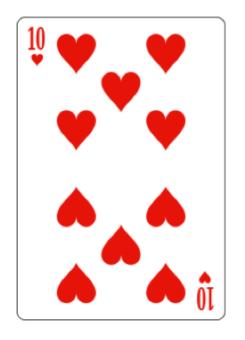


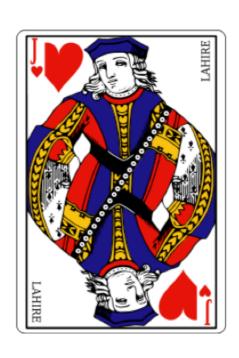






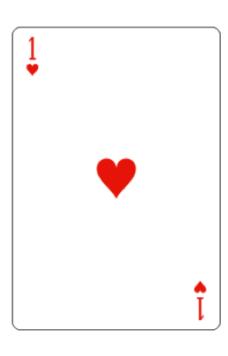
# How do you sort when playing cards?











## Sorting Algorithms

- Many different sorting algorithms, with different properties
- Given two items A and B, just need a comparator that can state which one is greater or equal
  - easy to say that 5 greater than 2, but what does it mean that song A is greater than song B? e.g., could look at alphabetic ordering of titles or artist names
- Most language APIs provides good defaults
  - Unless very large data, default will be fine 99% of the cases
- Sorting is very popular in programming
  - Important to understand how it works under the hood
- Tractable mathematically
  - So good example to show how to analyze algorithms

## Sorting Algorithms

- Bubble Sort
- Insertion Sort
- Merge Sort (next class)
- Quick Sort (next class)
- There are more, but those are the most famous that you need to know
- Good way to see a problem been solved in many different ways

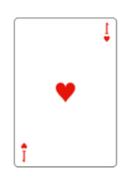
#### Bubble Sort

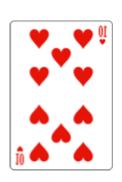
- Easiest sorting algorithms
- From left to right
- Look at adjacent cards, and swap them if not in order
- Repeat from left to right till no more swap











No swap, they are in order











Swap









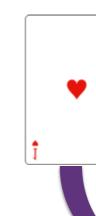


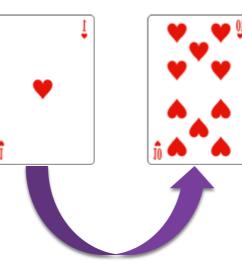
No swap, they are in order











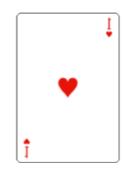












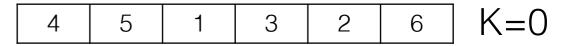
- Restart from beginning.
- At each iteration, at least one card will be in right position, as it bubbles up to the to top.

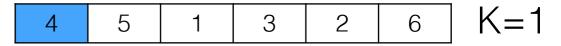
#### Runtime of Bubble Sort

- To sort N cards, need at most N iterations, in which you check at most N-1 pairs
- Even if already sorted, need to check each of N-1 pairs at least once, to see if indeed sorted
- $\Omega(N)$  and  $O(N^2)$  pair comparisons

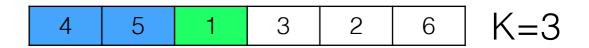
#### Insertion Sort

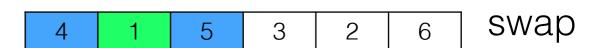
- An array of size 0 or 1 is always considered sorted
- From left to right, till length N
- K-leftmost values are sorted
- Position K+1 is not sorted, insert it in the first K
  - by swapping adjacent elements, like in Bubble Sort

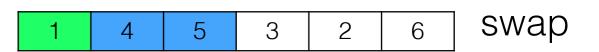




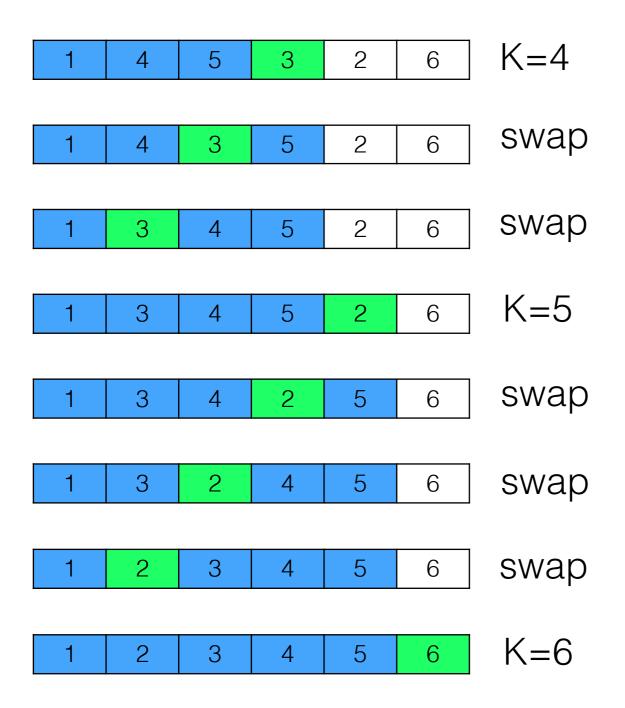








#### Cont.



- Best case: already sorted, e.g., 1-2-3-4-5-6, need to do N-1 comparisons, so Ω(N)
- Worst case: opposite order, e.g, 6-5-4-3-2-1, each element needs to be compared and swapped with all previous K ones, so O(N²)

#### Best vs. Worst Case

- "Best case" is not when N=0
- Runtime might not only depend on size N, but also on the content of the input
  - an array already sorted will likely take less time to sort than a shuffled one
  - on the other hand, summing all integers in an array will likely have no difference between Best and Worst case, ie Θ(N)
- Considering all possible inputs in a mathematical formula would not be viable
  - that is why we talk about BEST and WORST cases in relation to N

#### Homework

- Study Book Chapter 1.4 and 2.1
  - Note: in the book, the authors use the  $\sim$  notation instead of the standard O,  $\Omega$  and  $\Theta$ . They explain their reason in the Q&A for such weird choice, but I do disagree
- Study code in the org.pg4200.les03 package
- Do exercises in exercises/ex03
- Extra: do exercises in the book