



# Computational Complexity



What's important  
about Computational  
Complexity?



# Why complexity?

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- ▶ We have to decide between algorithm A and algorithm B
  - ▶ We have a dataset for benchmarking algorithms with about 1,000 rows
- ▶ What should we do?

	Algo A	Algo B
Time on lab data	5s	30s



# Why complexity?

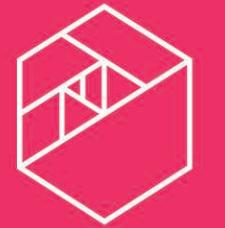
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  - ▶ This depends on what kinds of data the algorithms will be given *in production*
  - ▶ What if we'll be running it on 100k rows?

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- ▶  $t_a(n) = 5 * \left(\frac{n}{1000}\right)^2$

- ▶  $t_b(n) = 29 + \left(\frac{n}{1000}\right)$

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1k	5s	30s
10k	500s	39s
100k	13.9 hours	49s

# Complexity Defined

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- ▶ **Complexity**: An algorithm's complexity is a measure of the resources it uses
- ▶ Most common is **time complexity**
  - ▶ In a few weeks, we will discuss **space complexity** (memory use)

# Complexity Defined

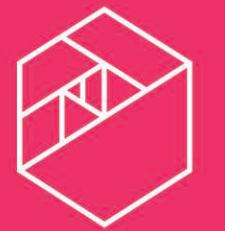
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- ▶ **Most common is time complexity**
  - ▶ In a few weeks, we will discuss space complexity (memory use)
- ▶ Time complexity can be measured in several ways
  - ▶ Wall clock measures amount of time that passes while the algorithm runs
    - ▶ Imminently useful
    - ▶ However, sensitive to details about hardware and implementation like processor core speed and parallelization

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    - ▶ Imminently useful
    - ▶ However, sensitive to details about hardware and implementation like processor core speed and parallelization
  - ▶ Compute time measures the computations made during the algorithm's execution
    - ▶ ex: number of comparisons, processor cycles
    - ▶ Relevant across different hardware setups and implementations



# Introducing Big-O Notation

# Big-O

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## Problem:

- ▶ We care about complexity but equations are difficult to compare
- ▶ Ex:
  - ▶  $f_a(n) = n^2 + 200n(n + \log(n))$   
vs
  - ▶  $f_b(n) = .01n^3$
- ▶ Do we care about which is faster at  $n = 10$  or  $n = 1,000$ ?

# Big-O

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## Solution

- ▶ Big-O notation simplifies comparisons of computational resources

# Big-O

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## Idea

- ▶ At scale, the most important comparison is the overall growth behavior
- ▶ For an equation like  $2^n + 4n^2$ , which part is going to matter as  $n \rightarrow \infty$ ?

# Big-O

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- ▶ At scale, the most important comparison is the overall growth behavior
- ▶ For an equation like  $2^n + 4n^2$ , which part is going to matter as  $n \rightarrow \infty$ ?

Complexity equations	
$2n!$	
$2^n + 4n^2$	
$n^{100} + 3$	
$n^2 + n$	

# Big-O



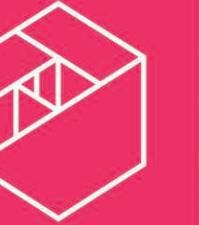
## Idea

## Definition

- ▶ If there exists a  $k$  and  $g(n)$  such that  $\lim_{n \rightarrow \infty} f(n) < kg(n)$
- ▶ Then  $f(n) = O(g(n))$

Complexity equations	What we care about
$2n!$	$2n!$
$2^n + 4n^2$	$2^n + 4n^2$
$n^{100} + 3$	$n^{100} + 3$
$n^2 + n$	$n^2 + n$

# Big-O



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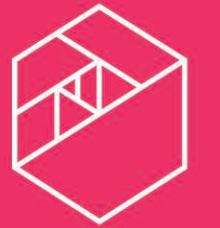
Complexity equations	What we care about	Big O
$2n!$	$2n!$	$O(n!)$
$2^n + 4n^2$	$2^n + 4n^2$	$O(2^n)$
$n^{100} + 3$	$n^{100} + 3$	$O(n^{100})$
$n^2 + n$	$n^2 + n$	$O(n^2)$



# Finding Big-O

# Using heuristics to find Big-O

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## Heuristic workflow

### 1. Find expression

- ▶ (more on how to find the expression in the notebook section)

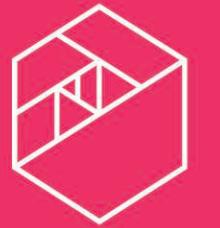
### 2. Simplify expression

### 3. Only keep highest order term

### 4. Discard constants

# Heuristics Cheat Sheet

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- ▶ **Coefficients**: Drop any constants / coefficients
  - ▶  $O(3N)$  is reduced to  $O(N)$
- ▶ **Simple statements**:  $O(1)$ 
  - ▶ `print()`
  - ▶ `dict['key'] = value`)
- ▶ **Loops**:  $O(\text{inside loop}) * \text{number of iterations}$
- ▶ **Consecutive statements**: Most complex statement on same indent
- ▶ **Conditional statements**:  $O(\text{condition} + \text{longest branch})$
- ▶ **Leading Terms**: Only keep the leading term
  - ▶  $O(N^2 + N)$  is reduced to  $O(N^2)$
- ▶ **Keep the furthest left term**:  $2n >> n^5 >> n^3 >> n^1 >> n \lg(n) >> \lg(n) >> 1$

# Finding Big-O (you try it)

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Find the big-O complexity for:

$$f(n) = n(2n + \sin(n))$$



# Finding Big-O

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Find the big-O complexity for:

$$f(n) = n(2n + \sin(n))$$

$$\rightarrow 2n^2 + n \sin(n) \quad [\text{simplify}]$$

$$\rightarrow 2n^2 \quad [\text{keep highest order term}]$$

$$\rightarrow n^2 \quad [\text{discard coefficients}]$$

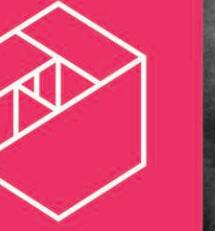
$$f(n) = O(n^2)$$



# Takeaways

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- ▶ Computational Complexity allows us to evaluate an algorithm's resource use
- ▶ Big-O notation is a tool for summarizing complexity in a useful way
- ▶ The Big-O complexity for an algorithm can be solved formally using proofs or informally using heuristics



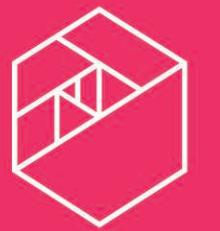
John Westrock



# Extras

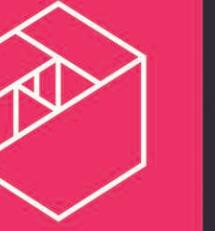
# Method 2: Proof

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## Proof

- ▶ Show that there exists a  $k_0$  and an  $n_0$  such that
  - ▶ For all  $n > n_0$ ,  $k_0 g(n) > f(n)$
  - ▶ Then  $f(n) = O(g(n))$



# Method 2 (you try it)

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Use a proof to find the big-O complexity of:

$$f(n) = \frac{1}{2}(2^n) - 3n$$

Let  $g(n) = 2^n$

$$k2^n > \frac{1}{2}(2^n) - 3n$$

$$k > \frac{1}{2} - \frac{3n}{2^n}$$

True for  $k = .5, n > 3$ , therefore  $f(n) = O(2^n)$  ■