# Algorithm Efficiency (More formally)

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### Today's Plan



Announcements

Midterm solution

Project 4 How are we doing?

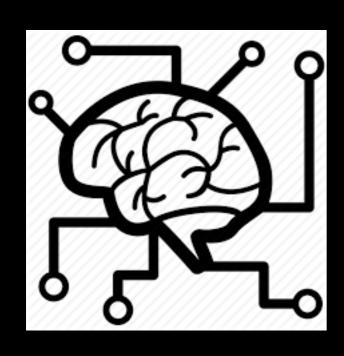
Algorithm Efficiency

## Announcements and Syllabus Check

Revised tentative schedule



### Midterm Solution



# Project 4: How are we doing?

## Algorithm Efficiency

You are using an app and suddenly it stalls... whatever it is doing it's taking way too long...

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how "long" does that have to be for you to become ridiculously frustrated?

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how "long" does that have to be for you to become ridiculously frustrated?

... probably not that long

At your next super high-end job with the company/research-center of your dreams you are given a very difficult problem to solve

You work hard on it, find a solution, code it up and it works!!!!

Proudly you present it the next day



but...

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but...

Given some new input it keeps stalling...

Well... sorry but your solution is no good!!!





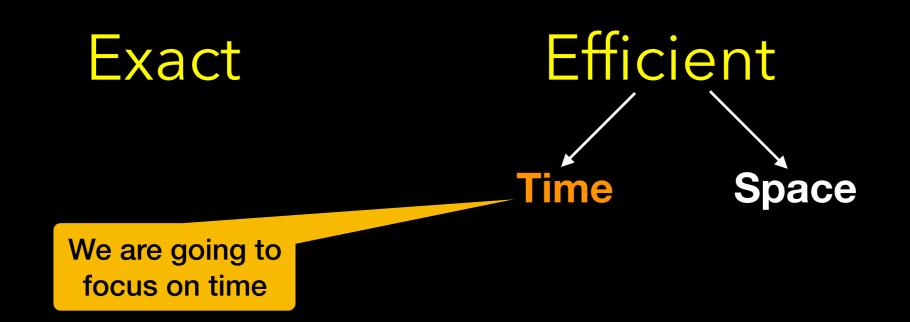
You need to have a means to estimate/predict the efficiency of your algorithms on unknown input.

How can we compare solutions to a problem? (Algorithms)

Exact

Exact Efficient

Time Space



# How can we measure time efficiency?

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Runtime?

# Problems with runtime for comparison

What computer are you using?

Runtime is highly sensitive to hardware

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#### What implementation are you using?

Implementation details may affect runtime but are not reflective of algorithm efficiency

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#### What data are you using?

Algorithm A may run faster on one dataset while algorithm B runs faster on another

## How should we measure execution time?

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Number of "steps" or "operations"

```
template < class ItemType>
void List < ItemType > :: traverse()
{
    for(Node < ItemType > * ptr = first; ptr != nullptr; ptr = ptr -> getNext())
    {
        std::cout << ptr -> getItem() << std::endl;
    }
}</pre>
```

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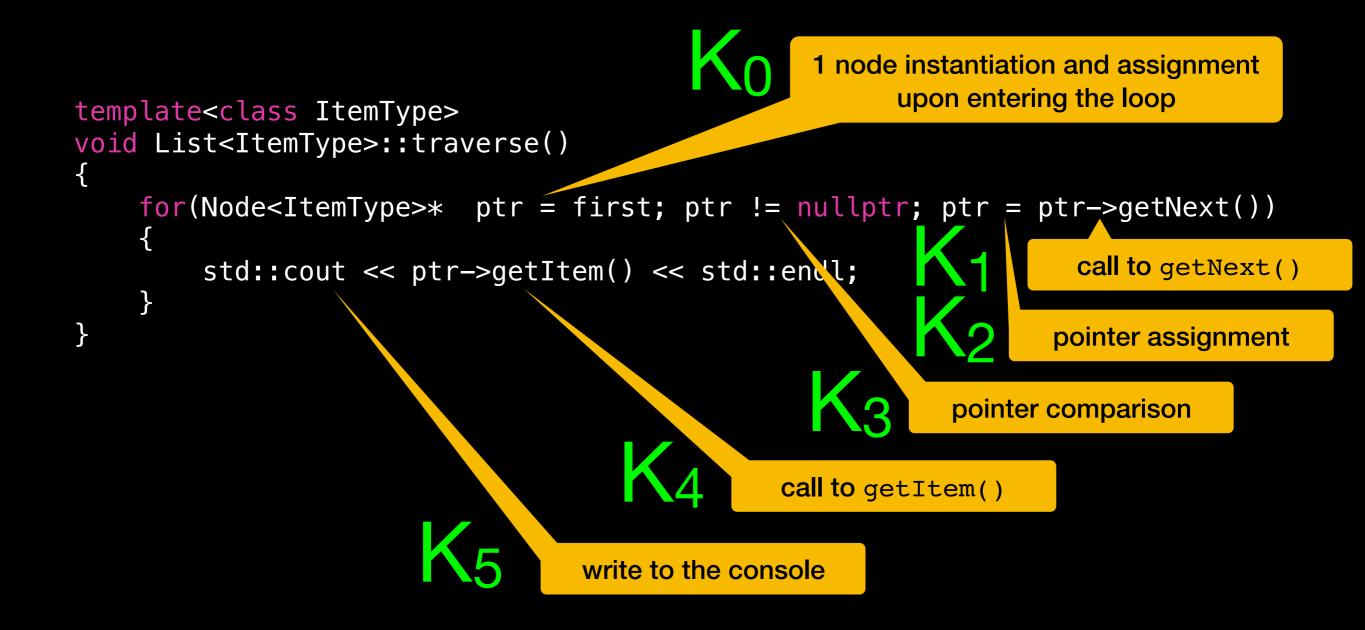
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pointer comparison

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}

pointer comparison</pre>
```

```
1 node instantiation and assignment
                                                          upon entering the loop
template<class ItemType>
void List<ItemType>::traverse()
    for(Node<ItemType>* ptr = first; ptr != nullptr; ptr = ptr->getNext())
                                                                       call to getNext()
         std::cout << ptr->getItem() << std::endl;</pre>
                                                                     pointer assignment
                                                              pointer comparison
                                                  call to getItem()
                                    write to the console
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Operations =  $K_0 + n(K_1+K_2+K_3+K_4+K_5)$ 

### In-Class Task

Identify the steps and write down an expression for execution time

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```
bool linearSearch(const std::string& str, char ch)
    for (int i = 0; i < str.length(); i++)</pre>
         <u>if</u> (str[i] == ch) {
                                                   Was this tricky?
             return true;
    return false;
```

#### n here is the length of the string

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```
bool linearSearch(const std::string& str, char ch)
{
     // 1 int assignment upon entering loop
    for (int i = 0; i < str.length(); i++)</pre>
    { // call to length() and increment
        if (str[i] == ch) { // Comparisons
             return true; //return operation, maybe
                                                 Maybe stop in
                                                  the middle
    return false; //return operation, maybe
                                      Maybe stop at
                                       end of loop
```

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             (str[i] == ch) {
         if
                                                           In the
              return true;
                                                        WORST CASE
                                                          it will be n
    return false;
                                 Execution completes in at most:
                                     k_0n+k_1 operations
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Some constant number of operations repeated inside the loop

Some constant number of operations performed outside the loop

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Execution completes in **at most:**  $k_0 \mathbf{n} + k_1$  operations

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## Observation

Don't need to explicitly compute the constants  $k_i$ 

$$4n + 1000$$

$$n + 137$$

Dominant term is sufficient to explain overall behavior (in this case linear)

## Ignores everything except dominant term

## Examples:

$$T(n) = 4n + 4 = O(n)$$
 $T(n) = 164n + 35 = O(n)$ 
 $T(n) = n^2 + 35n + 5 = O(n^2)$ 
 $T(n) = 2n^3 + 98n^2 + 210 = O(n^3)$ 
 $T(n) = 2^n + 5 = O(2^n)$ 

Notation: describes the overall WORST behavior

T(n) is the running time

N is the size of the input

Ignores everything except dominant term

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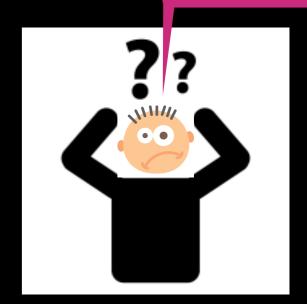
Big-O describes the overall WORST behavior

Let T(n) be the **running time** of an algorithm measured as number of operations given **input of size n**. T(n) is O(f(n))

if it grows **no faster** than f(n)

But 164n+35 > n

## Big-O Notation



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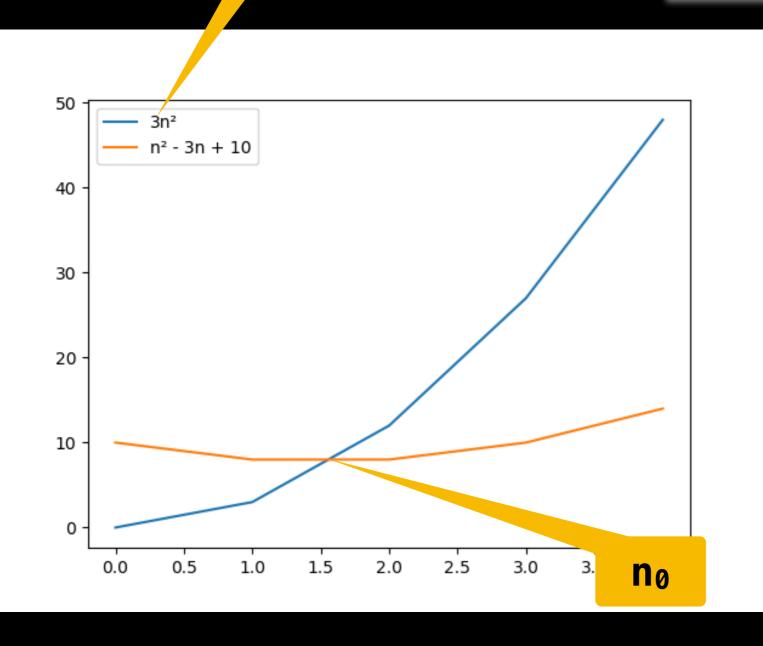
More formally: T(n) is O(f(n))if there exist constants k and  $n_0$ such that for all  $n \ge n_0$   $T(n) \le kf(n)$ 

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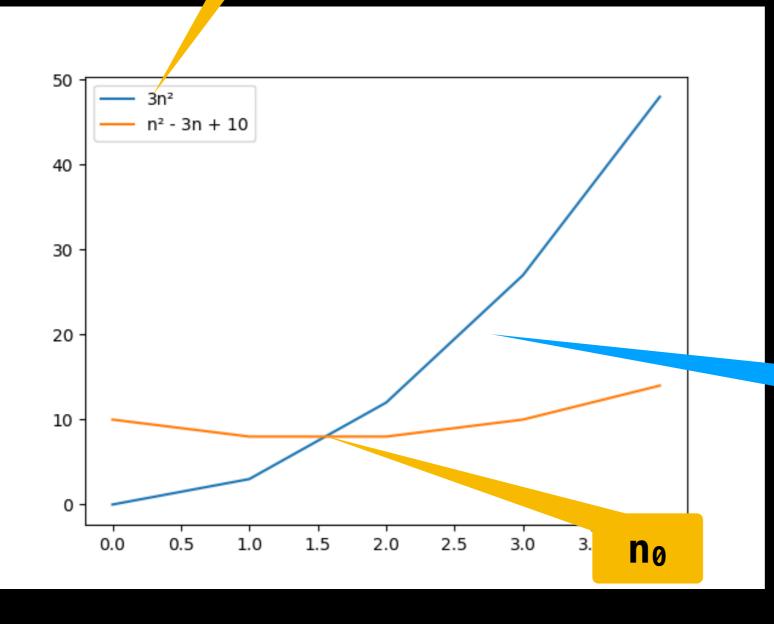
 $T(n) = n^2 - 3n + 10$  T(n) is  $O(n^2)$ For k=3 and  $n \ge 1.5$ 

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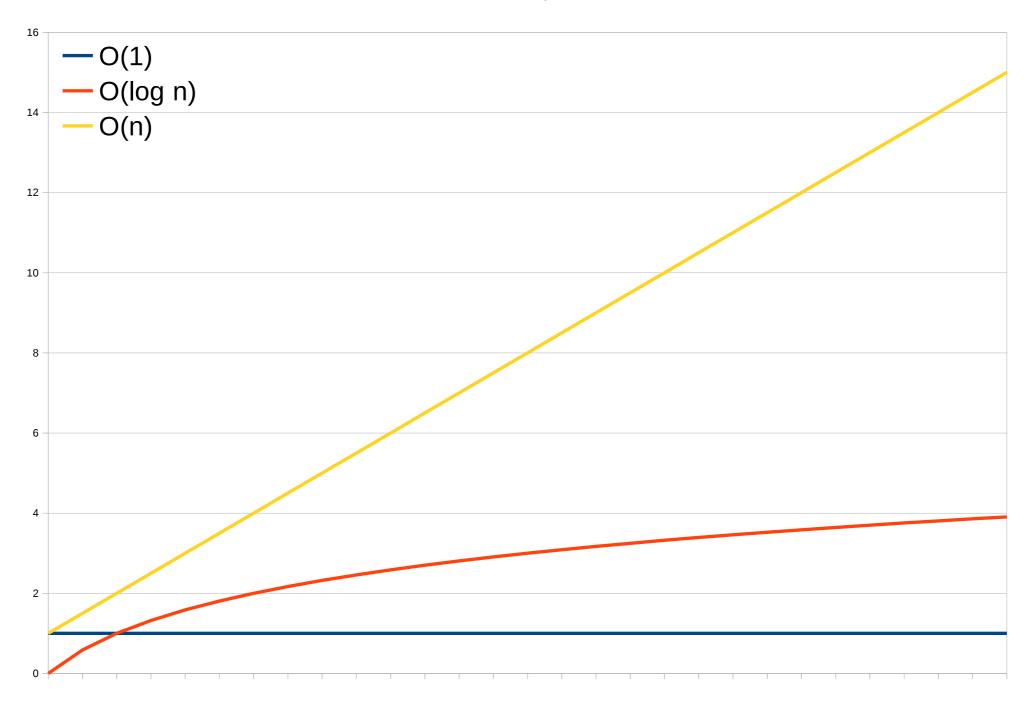
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This is why we can look at dominant term only to explain behavior

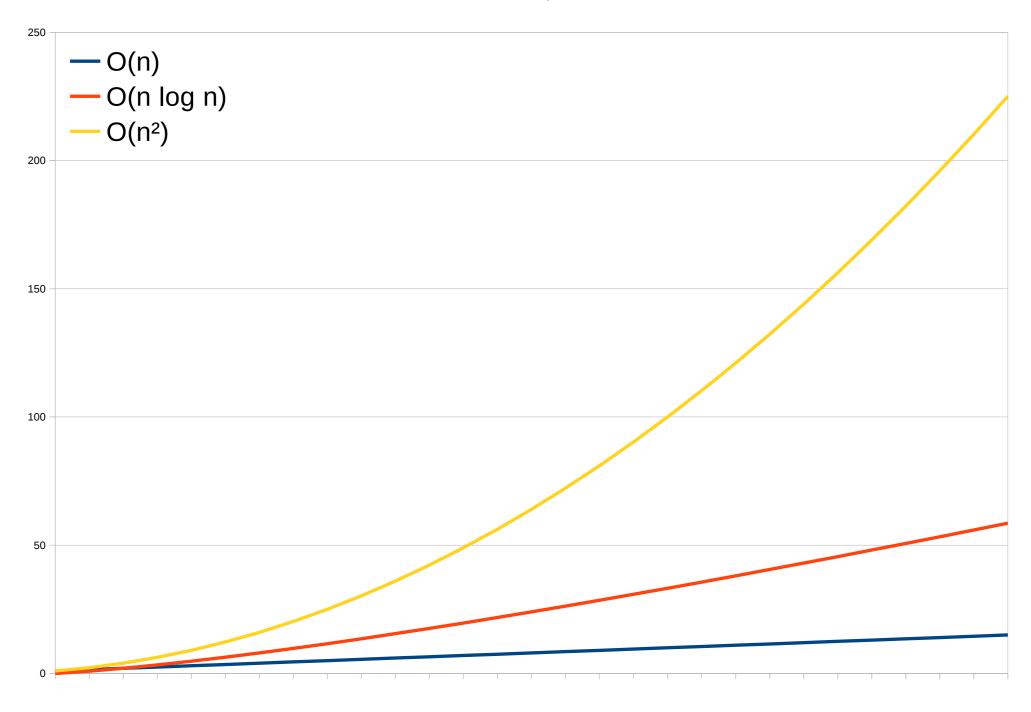
Big-O describes the worst-case overall growth rate of an algorithms for large n

# A visual comparison of growth rates

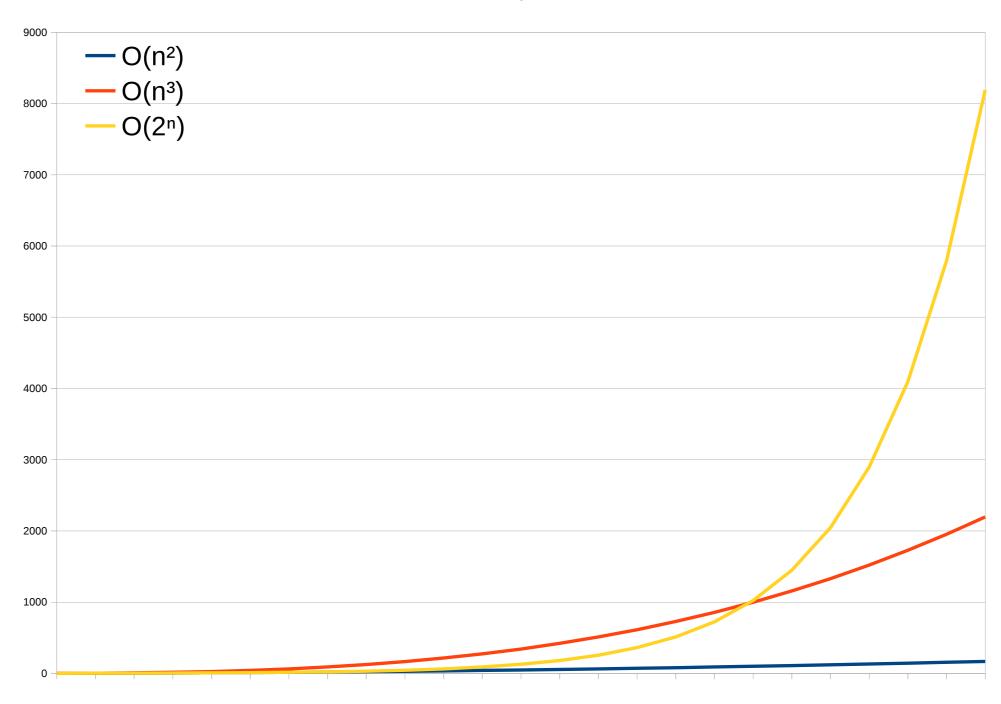
#### Growth Rates, Part One



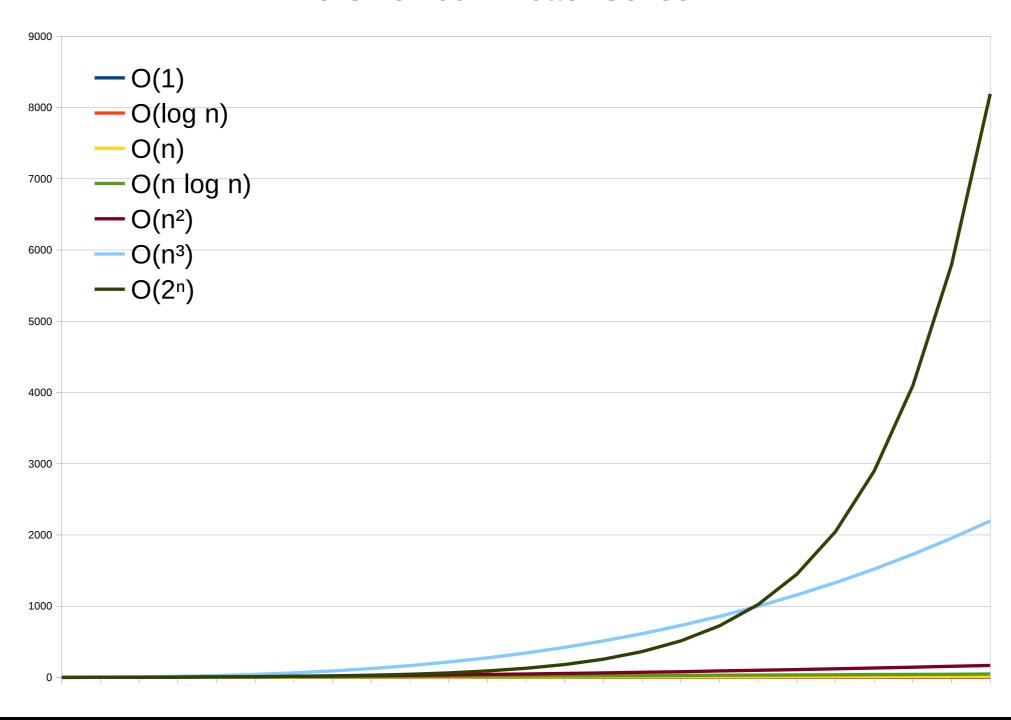
#### Growth Rates, Part Two



#### Growth Rates, Part Three



#### To Give You A Better Sense...



# A numerical comparison of growth rates

n Function	10	100	1,000	10,000	100,000	1,000,000
1	1	1	1	1	1	1
log <sub>2</sub> n	3	6	9	13	16	19
n	10	10 <sup>2</sup>	10 <sup>3</sup>	104	105	10 <sup>6</sup>
n * log <sub>2</sub> n	30	664	9,965	105	106	107
n²	<b>10</b> <sup>2</sup>	104	10 <sup>6</sup>	108	<b>10</b> <sup>10</sup>	<b>10</b> <sup>12</sup>
n <sup>3</sup>	10 <sup>3</sup>	10 <sup>6</sup>	10 <sup>9</sup>	<b>10</b> <sup>12</sup>	<b>10</b> <sup>15</sup>	<b>10</b> <sup>18</sup>
<b>2</b> n	10 <sup>3</sup>	<b>10</b> <sup>30</sup>	<b>10</b> <sup>301</sup>	<b>10</b> 3,010	<b>10</b> 30,103	<b>10</b> 301,030

# What does Big-O describe?

## "Long term" behavior of a function

Compare behavior of 2 algorithms

If algorithm A has runtime O(n) and algorithm B has runtime  $O(n^2)$ , for large inputs A will always be faster.

If algorithm A has runtime O(n), for large inputs doubling the size of the input will double the runtime

Analyze algorithm behavior with growing input

# What can't Big-O describe?

The actual runtime of an algorithm

$$10^{100}n = O(n)$$

$$10^{-100}n = O(n)$$

How an algorithm behaves on small input

$$n^3 = O(n^3)$$

$$10^6 = O(1)$$

# Types of Analysis

```
Big-O: worst-case analysis T(n) is O(f(n))
```

Grows no faster than f(n)

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Omega: best-case analysis

T(n) is  $\Omega(f(n))$ 

Grows at least as fast as f(n)

Useful to know if algorithm performs well in some cases

# Types of Analysis

```
T(n) is O(f(n))
    Grows no faster than f(n)
    It can't get worst than this, good for "sleeping well at night"
Omega: best-case analysis
    T(n) is \Omega(f(n))
    Grows at least as fast as f(n)
    Useful to know if algorithm performs well in some cases
Theta: average-case analysis
   T(n) is \Theta(f(n))
    Grows at the same rate as f(n): is both O(f(n)) and \Omega(f(n))
    The most exact but far more difficult, must determine relative
    probabilities of problem sizes or distribution of data values
```

Big-O: worst-case analysis

# To summarize Big-O

It is a means of describing the growth rate of a function

It ignores all but the dominant term

It ignores constants

Allows for quantitative ranking of algorithms

Allows for quantitative reasoning about algorithms

# More examples next time