#### **Fundamentals**

## SFWRENG 2CO3: Data Structures and Algorithms

Jelle Hellings

Department of Computing and Software McMaster University



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*Engineering* is the application of science and mathematics to solve practical problems.

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#### Software engineering requires

- ▶ a deep understanding of what software (programs) do;
- mastery of a toolbox of fundamental tools to tackle programming challenges;
- ► capability to *analyze* software in depth.

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This course introduces the analysis of software by studying and analyzing fundamental tools.

- ► Analysis of algorithms and data structures: *correctness* and *complexity*.
- Common design strategies for algorithms and data structures.
- ► A useful toolbox of standard fundamental algorithms and data structures.
- Graph representations and fundamental graph algorithms.

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## Software engineering requires

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This course is *not* about learning how to program (basic programming is prior knowledge).

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## Definition (Algorithm)

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## Definition (Data structure)

Scheme to store and organize data in order to facilitate *efficient* access and modification.

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For *optimal* implementations, we sometimes need a lower-level toolbox. E.g., references or pointers when implementing data structures.

Many programming languages suffice, e.g.,

- the book has many examples in Java;
- ► I will provide some examples in C++.

Feel free to experiment in your programming language of choice.

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Given a list L and value v, return  $v \in L$ .

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# **Algorithm** Contains(L, v):

```
1: i, r := 0, false.

2: while i \neq |L| do

3: if L[i] = v then

4: r := \text{true}.

5: i := i + 1.

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7: i := i + 1.

8: return r.
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```

**Result:** return true if  $v \in L$  and false otherwise.

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#### Problem

Given a list L and value v, return  $v \in L$ .

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Algorithm Contains(L, v):
```

**Input:** *L* is an *array*, *v* a value.

```
1: i, r := 0, false.
```

2: while 
$$i \neq |L|$$
 do

$$: \quad \text{if } L[i] = v \text{ then }$$

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$$r := \text{true}$$
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**Result:** return true if  $v \in L$  and false otherwise.

Is Contains correct?

#### Problem

Given a list L and value v, return  $v \in L$ .

# **Algorithm** EVILCONTAINS(L, v):

**Input:** L is an array, v a value.

1: L := [].

2: return false.

**Result:** return true if  $v \in L$  and false otherwise.

Is EVILCONTAINS correct?

#### Problem

Given a list L and value v, return  $v \in L$ .

# **Algorithm** Contains(L, v):

```
1: i, r := 0, false.
```

- 2: while  $i \neq |L|$  do
  - if L[i] = v then
- 4: r := true.
- 5: i := i + 1.
- 6: **else**
- 7: i := i + 1.
- 8: return r.

#### Problem

Given a list L and value v, return  $v \in L$ .

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 1: i, r := 0, false.
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        i := i + 1.
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5/1

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    /* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
 2: while i \neq |L| do
     if L[i] = v then
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  5.
    else
         i := i + 1.
    /* r is true if v \in L and false otherwise. */
  8: return r.
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5/1

#### Prove the invariant holds

```
/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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Prove the invariant holds /\* inv:  $0 \le i \le |L|$ ,  $v \in L[0,i)$  implies r =true,  $v \notin L[0,i)$  implies r =false. \*/

Proof by induction

6/1

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## Proof by induction

Base case Prove invariant holds before the loop.

Hypothesis The invariant holds after the j-th, j < m, repetition of the loop.

Step Assume invariant holds when we start the *m*-th repetition of the loop. Prove invariant holds again when we reach the end of the *m*-th repetition.

6/1

```
Prove the invariant holds /* inv: 0 \le i \le |L|, v \in L[0,i) implies r = \text{true}, v \notin L[0,i) implies r = \text{false}. */
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```

# Base case: Prove invariant holds before the loop

**Input:** *L* is an *array*, *v* a value.

```
1: i, r := 0, false.

/* L is an array, v a value, i = 0, and r = false. */
```

2: **while** ....

## Argument

1. L[0, i) with i = 0 is L[0, 0).

#### Prove the invariant holds

```
/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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1: i, r := 0, false.

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2: **while** ....

- 1. L[0, i) with i = 0 is L[0, 0).
- 2. L[0,0) is empty, hence  $v \notin L[0,0)$ .

#### Prove the invariant holds

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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2: **while** ....

- 1. L[0, i) with i = 0 is L[0, 0).
- 2. L[0,0) is empty, hence  $v \notin L[0,0)$ .
- 3. Hence, r =false must hold (which is the case).

# Prove the invariant holds /\* inv: $0 \le i \le |L|$ , $v \in L[0,i)$ implies r =true, $v \notin L[0,i)$ implies r =false. \*/

Step: Prove invariant holds again when we reach the end of the *m*-th repetition.

```
    2: while i ≠ |L| do
        /* Invariant and i ≠ |L|. */
    3: if L[i] = v then
    4: r := true.
    5: i := i + 1.
    6: else
    7: i := i + 1.
        /* Invariant. */
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#### Argument

If-statement: Case distinction.

```
Prove the invariant holds

/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */

Case distinction: If-case (L[i] = v holds).

3: if L[i] = v then

/* Invariant, i \ne |L|, and L[i] = v */

4: r := \text{true}.

5: i := i + 1.

/* Invariant. */
```

#### Argument

After Line 5: prove that Invariant holds for the *updated* values  $r_{new}$ ,  $i_{new}$  of r and i.

#### Prove the invariant holds

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- 4: r := true.
- 5: i := i + 1. /\* Invariant. \*/

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1. L[i] = v, hence,  $v \in L[0, i]$ .

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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- 1. L[i] = v, hence,  $v \in L[0, i]$ .
- 2.  $i_{\text{new}} = i + 1$ , hence,  $v \in L[0, i_{\text{new}})$ .

#### Prove the invariant holds

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- 2.  $i_{\text{new}} = i + 1$ , hence,  $v \in L[0, i_{\text{new}})$ .
- 3. Hence,  $r_{\text{new}} = \text{true must hold (which is the case)}$ .

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/* inv: 0 \le i \le |L|, v \in L[0,i) implies r = \text{true}, v \notin L[0,i) implies r = \text{false}. */

Case distinction: If-case (L[i] = v holds).

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4: r := \text{true}.

5: i := i + 1.

/* Invariant. */
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#### Argument

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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Case distinction: If-case (L[i] = v holds).

```
3: if L[i] = v then

/* Invariant, i \neq |L|, and L[i] = v */
```

- 4: r := true.
- 5: i := i + 1. /\* Invariant. \*/

#### Argument

After Line 5: prove that Invariant holds for the *updated* values  $r_{new}$ ,  $i_{new}$  of r and i.

- 1.  $0 \le i \le |L|$  and  $i \ne |L|$  implies  $0 \le i < |L|$ .
- 2.  $i_{\text{new}} = i + 1$ , hence,  $0 < i_{\text{new}} \le |L|$ .
- 3.  $0 < i_{\text{new}} \le |L| \text{ implies } 0 \le i_{\text{new}} \le |L|$ .

# Prove the invariant holds /\* inv: $0 \le i \le |L|$ , $v \in L[0, i)$ implies r = true, $v \notin L[0, i)$ implies r = false. \*/ Case distinction: Else-case ( $L[i] \ne v$ holds). 6: if L[i] = v then ...else /\* Invariant, $i \ne |L|$ , and $L[i] \ne v */$ 7: i := i + 1. /\* Invariant. \*/

#### Argument

#### Prove the invariant holds

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
```

Case distinction: Else-case ( $L[i] \neq v$  holds).

```
    6: if L[i] = v then ...else
        /* Invariant, i ≠ |L|, and L[i] ≠ v */
    7: i := i + 1.
        /* Invariant, */
```

## Argument

After Line 7: prove that Invariant holds for the *updated* value  $i_{new}$  of i.

1. Assume r = true. Hence,  $v \in L[0, i)$  by the invariant.

#### Prove the invariant holds

```
/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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Case distinction: Else-case ( $L[i] \neq v$  holds).

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    6: if L[i] = v then ...else
        /* Invariant, i ≠ |L|, and L[i] ≠ v */
    7: i := i + 1.
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#### Argument

- 1. Assume r = true. Hence,  $v \in L[0, i)$  by the invariant.
- 2.  $i_{\text{new}} = i + 1$ , hence,  $v \in L[0, i_{\text{new}})$ .

#### Prove the invariant holds

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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7: 
$$i := i + 1$$
.  
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#### Argument

- 1. Assume r = true. Hence,  $v \in L[0, i)$  by the invariant.
- 2.  $i_{\text{new}} = i + 1$ , hence,  $v \in L[0, i_{\text{new}})$ .
- 3. Hence, r = true must hold (which is the case).

#### Prove the invariant holds

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
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Case distinction: Else-case ( $L[i] \neq v$  holds).

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6: if L[i] = v then ... else

/* Invariant, i \neq |L|, and L[i] \neq v */
```

#### Argument

- 1. Assume r = false. Hence,  $v \notin L[0, i)$  by the invariant.
- 2.  $i_{\text{new}} = i + 1$  and  $L[i] \neq v$ , hence,  $v \notin L[0, i_{\text{new}})$ .
- 3. Hence, r = false must hold (which is the case).

# We have proven the invariant holds

```
/* inv: 0 ≤ i ≤ |L|, v ∈ L[0, i) implies r = true, v ∉ L[0, i) implies r = false. */
6: while i ≠ |L| do ... end while
/* Invariant and ¬(i ≠ |L|). */
/* r is true if v ∈ L and false otherwise. */
7: return r.
```

Are we done?

# We have proven the invariant holds

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
6: while i \ne |L| do ... end while

/* Invariant and \neg (i \ne |L|). */

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7: return r.
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#### Are we done?

► Assuming /\* Invariant and  $\neg(i \neq |L|) */$ ,

Do we have /\* r is true if  $v \in L$  and false otherwise \*/?

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► Assuming /\* Invariant and  $\neg(i \neq |L|)$  \*/, Do we have /\* r is true if  $v \in L$  and false otherwise \*/?

```
1. \neg (i \neq |L|) implies i = |L|.
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/* inv: 0 ≤ i ≤ |L|, v ∈ L[0, i) implies r = true, v ∉ L[0, i) implies r = false. */
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- 1.  $\neg (i \neq |L|)$  implies i = |L|.
- 2. L[0, i) with i = |L| is equivalent to L.

## We have proven the invariant holds

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- 1.  $\neg (i \neq |L|)$  implies i = |L|.
- 2. L[0, i) with i = |L| is equivalent to L.
- 3. Hence,  $v \in L$  implies r = true,  $v \notin L$  implies r = false.

# We have proven the invariant holds

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/* inv: 0 ≤ i ≤ |L|, v ∈ L[0, i) implies r = true, v ∉ L[0, i) implies r = false. */
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/* Invariant and ¬(i ≠ |L|). */
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7: return r.
```

#### Are we done?

- ► Assuming /\* Invariant and  $\neg(i \neq |L|)$  \*/,

  Do we have /\* r is true if  $v \in L$  and false otherwise \*/?  $\longrightarrow$  Yes!
- ▶ Do we reach the end of the loop?

#### Are we done?

► Do we reach the end of the loop?

```
2: i, r := 0, false.

3: while i \neq |L| do

4: if L[i] = v then

5: r := \text{true}.

6: i := i + 1.

7: else

8: i := i + 1.
```

#### Are we done?

▶ Do we reach the end of the loop?  $\longrightarrow$  *Yes*—obviously *i* will only be 0, ..., |L|.

```
2: i, r := 0, false.

3: while i \neq |L| do

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7/

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## Formal argument: prove a bound function

Define a *bound function* f on the state of the algorithm such that the output of f:

- ightharpoonup is a natural number (0, 1, 2, ...).
- strictly decreases after each iteration of the loop body.

#### Are we done?

▶ Do we reach the end of the loop?  $\longrightarrow$  Yes—obviously i will only be 0, ..., |L|.

```
    2: i, r := 0, false.
    3: while i ≠ |L| do /* bound function: |L| - i */
    4: if L[i] = v then
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Define a *bound function* f on the state of the algorithm such that the output of f:

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- strictly decreases after each iteration of the loop body.

#### Are we done?

▶ Do we reach the end of the loop?  $\longrightarrow$  Yes—obviously i will only be 0, ..., |L|.

```
2: i, r := 0, false. \longleftrightarrow |L| - i \text{ starts at } |L|, |L| \ge 0.

3: while i \ne |L| do /* bound function: |L| - i */

4: if L[i] = v then

5: r := \text{true}.

6: i := i + 1. \longleftrightarrow |L| - i \text{ strictly decreases}.

7: else

8: i := i + 1. \longleftrightarrow |L| - i \text{ strictly decreases}.
```

#### Formal argument: prove a bound function

Define a bound function f on the state of the algorithm such that the output of f:

- $\blacktriangleright$  is a *natural number* (0, 1, 2, ...).
- strictly decreases after each iteration of the loop body.

## Summary

- ▶ Define a *pre-condition*: What restrictions do we require on the input?
- ▶ Define a *post-condition*: What should the output be?
- ▶ Prove that *running the program* turns the pre-condition into the post-condition.

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8/1

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/* inv: 0 \le i \le |L|, v \in L[0, i) implies r = \text{true}, v \notin L[0, i) implies r = \text{false}. */
3: while i \ne |L| ... end while

/* r is true if v \in L and false otherwise */
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# A simple algorithm: Contains

#### Problem

Given a list L and value v, return  $v \in L$ .

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Algorithm Contains(L, v):

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3:
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0/1

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NumInstr(
$$N$$
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A *scientific model* allows predictions

Assume: Contains with a list L, |L| = 1000, takes  $12 \,\mu s$ .

*Predict*: How long does Contains take with a list of 2000 values?

- 1. NumInstrOnlyElse(1000) = 7005 instructions  $\longrightarrow$  12  $\mu$ s.
- 2. NumInstrOnlyElse(2000) = 14 005 instructions →

$$\frac{14005}{7005} \cdot 12 \,\mu s \approx 2 \cdot 12 \,\mu s = 24 \,\mu s.$$

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- ► Are our predictions correct?
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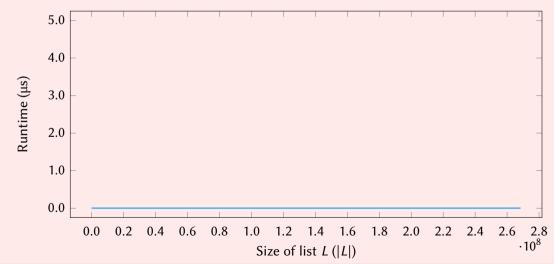
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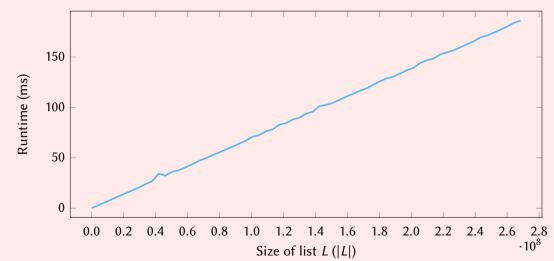
#### Useful models are *simple* and make *correct* predictions

- ► Are our predictions correct? Lets implement Contains and measure.
- ► Is our model simple?

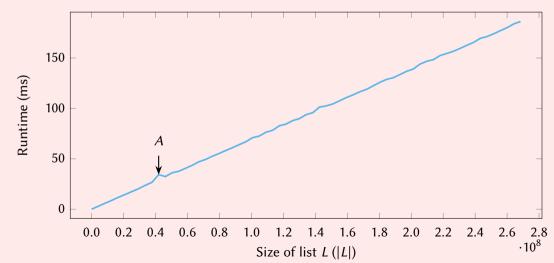
#### First Attempt



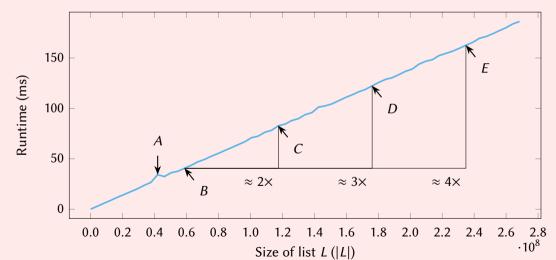




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Useful models are *simple* and make *correct* predictions

- ► Are our predictions correct? *Yes.*
- ▶ Is our model simple?  $\longrightarrow$  *No: Runtime*(N) = N *predicts the same!*

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Useful models are *simple* and make *correct* predictions

- ► Are our predictions correct? *Yes.*
- Is our model simple? → No: Runtime(N) = N predicts the same! Also: Our instruction counting is mostly fiction!

### A simple algorithm: Contains

#### Problem

Given a list L and value v, return  $v \in L$ .

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1: i, r := 0, false.

2: while i \neq |L| do

3: if L[i] = v then

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5: i := i + 1.

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7: i := i + 1.
```

#### Theorem

8: return r.

Contains is correct, its runtime complexity is modelled by ContainsRuntime(|L|) = |L|, and its memory complexity is modelled by ContainsMemory(|L|) = 1.

Say we have two algorithms for the *contains* problem

- Contains with C.Runtime(|L|) = |L|.
- ALTC with AltCRuntime(|L|) =  $|L|^2$ .

Which one is *faster*?

Can we conclude that Contains is always fastest, ALTC is slowest?

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Runtime Contains Runtime AltC	12 μs 3 μs
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Input size	1000	2000
Runtime Contains Runtime AltC	12 μs 3 μs	24 μs 12 μs
Speed up of ALTC	4×	2×

- C.Runtime(2000) =  $2000 = 2 \cdot 1000 = 2 \cdot \text{C.Runtime}(1000)$ .
- ► AltCRuntime(2000) =  $2000^2 = 2^2 \cdot 1000^2 = 2^2 \cdot \text{AltCRuntime}(1000)$ .

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Input size	1000	2000	4000	
Runtime Contains Runtime AltC	12 μs 3 us	24 μs 12 us	48 μs 48 us	
Speed up of ALTC				

- C.Runtime(4000) =  $4000 = 4 \cdot 1000 = 4 \cdot C.Runtime(<math>1000$ ).
- ► AltCRuntime(4000) =  $4000^2 = 4^2 \cdot 1000^2 = 4^2 \cdot AltCRuntime(1000)$ .

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Input size	1000	2000	4000	8000	
Runtime Contains Runtime AltC	12 μs 3 μs	24 μs 12 μs	48 μs 48 μs	96 μs 192 μs	
Speed up of ALTC	4×	$2\times$	1×	0.5×	

- C.Runtime(8000) =  $8000 = 8 \cdot 1000 = 8 \cdot C.Runtime(<math>1000$ ).
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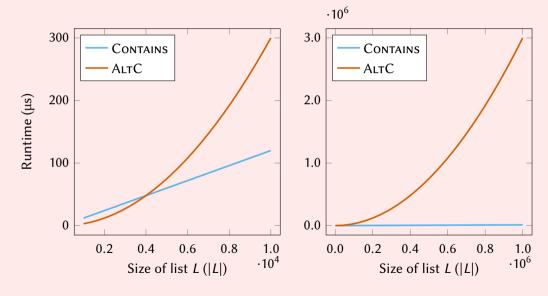
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Runtime Contains Runtime AltC	12 μs 3 μs	24 μs 12 μs	48 μs 48 μs	96 μs 192 μs	12 ms 3000 ms
Speed up of ALTC	4×	2×	1×	0.5×	0.004×

- ightharpoonup C.Runtime(1000000) = 10000000 = 1000 · 1000 = 1000 · C.Runtime(1000).
- ► AltCRuntime( $1000\,000$ ) =  $1000000^2 = 1000^2 \cdot 1000^2 = 1000^2 \cdot \text{AltCRuntime}(1000)$ .



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Are our models meaningless?

No: our comparisons shows differences in growth rates: |L| versus  $|L|^2 \longrightarrow$  for large-enough inputs, ALTC should always be *much slower* than CONTAINS.

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Remember: We are interested in *scalability* of algorithms

For large-enough inputs, Contains will always be much faster than AltC *because* the order of growth of C.Runtime is *lower* than the order of growth of AltCRuntime.

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Runtime complexi	ty (size of input: <i>N</i> ) ALGORITHM 2	Which is faster? (for large-enough N)
5 + 7 <i>N</i>	3N + 100	· · · · · · · · · · · · · · · · · · ·
5 + 7 <i>N</i>	$100 \log_2(N) + 2$	
5 + 7 <i>N</i>	N(N-1)/2	
5 + 7 <i>N</i>	$1000N^{\frac{1}{2}}-120$	
$2N^3 + 1000$	$2^{N} - 1$	

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5 + 7 <i>N</i>	$1000N^{\frac{1}{2}}-120$	Algorithm 2
$2N^3 + 1000$	2 <sup>N</sup> – 1	Algorithm 1

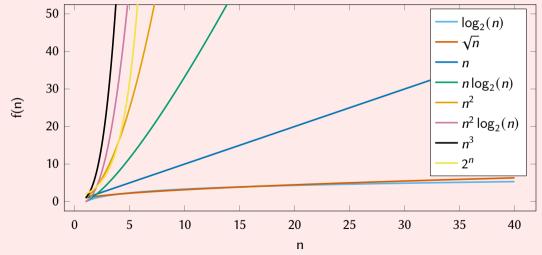
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Runtime complexi	ty (size of input: N)	Which is faster?
Algorithm 1	Algorithm 2	(for large-enough N)
N	N	Similar
N	ln(N)	Algorithm 2
N	$N^2$	Algorithm 1
N	$\sqrt{N}$	Algorithm 2
$N^3$	2 <sup>N</sup>	Algorithm 1

Simpler models are easier to compare!

Some very common functions f(n)—(increasing order of growth)



#### Definition (informal)

Let *f* and *g* be functions of size of input *n*:

- 1. f(n) = O(g(n)) denotes f "scales better" than g(n). The order of growth of f is *upper bounded* by g: any increase in the runtime predicted by f as a consequence of increasing f is f increase predicted by f increase predicted by
- 2.  $f(n) = \Omega(g(n))$  denotes f "scales worse" than g(n). The order of growth of f is *lower bounded* by g: any increase in the runtime predicted by f as a consequence of increasing f is f is at-least the increase predicted by f increase f increase
- 3.  $f(n) = \Theta(g(n))$  denotes f "scales the same" as g(n).

  The order of growth of f is *equivalent* to g: any increase in the runtime predicted by f as a consequence of increasing n is *equivalent* to the increase predicted by g(n). In this case, we also say that f(n) is *strictly bounded by* g(n).

The book uses the notation  $f(n) \sim (g(n))$  instead of  $f(n) = \Theta(g(n))$ .

#### Definition (formal)

Let *f* and *g* be functions of size of input *n*:

1. f(n) = O(g(n)) if there exists constants  $n_0$ , c > 0 such that

$$0 \le f(n) \le c \cdot g(n)$$
 for all  $n \ge n_0$ .

2.  $f(n) = \Omega(g(n))$  if there exists constants  $n_0$ , c > 0 such that,

$$0 \le c \cdot g(n) \le f(n)$$
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3.  $f(n) = \Theta(g(n))$  if there exists constants  $n_0$ ,  $c_{lb}$ ,  $c_{ub} > 0$  such that,

$$0 \le c_{\mathsf{lb}} \cdot g(n) \le f(n) \le c_{\mathsf{ub}} \cdot g(n)$$
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Constant  $n_0$  allows us to only look at large inputs (larger than  $n_0$ ). Example,  $n^2 > n$  only when inputs are large enough!

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#### Constants $n_0$ ? c?

- Constant  $n_0$  allows us to *only* look at large inputs (larger than  $n_0$ ). Example,  $n^2 > n$  only when inputs are large enough!
- Constant c hides "irrelevant details". Example,  $3 + 7 \cdot n$  and  $n \mod l$  the same behavior!

#### Definition (formal)

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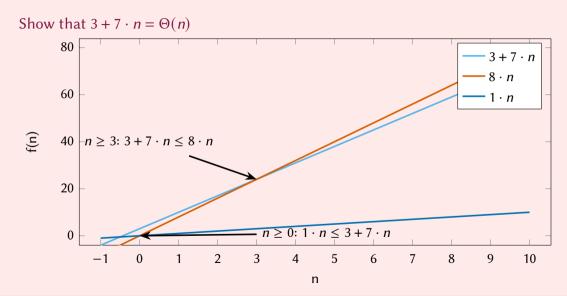
$$0 \le f(n) \le c \cdot g(n)$$
 for all  $n \ge n_0$ .

Show that 
$$3 + 7 \cdot n = O(n)$$

▶  $3 + 7 \cdot n = O(n)$ . Choose  $n_0 = 3$  and c = 8. The statement

for all 
$$n \ge 3$$
,  $0 \le 3 + 7 \cdot n \le 8 \cdot n$ 

is true, completing the proof.



#### Theorem

- ► The runtime complexity of Contains is  $\Theta(|L|)$ .
- ► The memory complexity of Contains is  $\Theta(1)$ .

How to compare the order of growth of functions?

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Limits: A mathematical power tool Let *f* and *g* be functions of *n* with non-negative ranges. If

$$\lim_{n\to\infty}\frac{f(n)}{g(n)} \text{ is defined and is } \begin{cases} \infty & \text{then } f(n)=\Omega(g(n));\\ c, \text{ with } c>0 \text{ a constant} & \text{then } f(n)=\Theta(g(n));\\ 0 & \text{then } f(n)=O(g(n)). \end{cases}$$

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#### Example

$$\lim_{n \to \infty} \frac{c \cdot f(n)}{f(n)} = c \cdot \left(\lim_{n \to \infty} \frac{f(n)}{f(n)}\right) = c$$

4/1

Limits: A mathematical power tool Let *f* and *g* be functions of *n* with non-negative ranges. If

$$\lim_{n\to\infty}\frac{f(n)}{g(n)} \text{ is defined and is } \begin{cases} \infty & \text{then } f(n)=\Omega(g(n));\\ c, \text{ with } c>0 \text{ a constant} & \text{then } f(n)=\Theta(g(n));\\ 0 & \text{then } f(n)=O(g(n)). \end{cases}$$

## Example

$$\lim_{n \to \infty} \frac{c \cdot f(n)}{f(n)} = c \cdot \left(\lim_{n \to \infty} \frac{f(n)}{f(n)}\right) = c \longrightarrow c \cdot f(n) = \Theta(f(n))$$

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Example (See Example 3.26 in the course notes for details)

$$\log_{a}(n) = \frac{\log_{b}(n)}{\log_{b}(a)} = \frac{1}{\log_{b}(a)} \cdot \log_{b}(n) \qquad \longrightarrow \log_{a}(n) = \Theta(\log_{b}(n))$$

$$\lim_{n \to \infty} \frac{\log_{2}(n)^{c}}{n^{d}} = 0 \qquad \longrightarrow \log_{2}(n)^{c} = O(n^{d})$$

$$\lim_{n \to \infty} \frac{d^{n/u}}{c^{n/v}} = 0 \text{ (if } c \ge d \ge 1, u \ge v \ge 1) \qquad \longrightarrow d^{n/u} = O(c^{n/v})$$

$$\lim_{n \to \infty} \frac{c_{1}n^{d_{1}} + \dots + c_{m}n^{d_{m}}}{n^{d_{i}}} = c_{i} (d_{i} = \max(d_{1}, \dots, d_{m})) \qquad \longrightarrow c_{1}n^{d_{1}} + \dots + c_{m}n^{d_{m}} = \Theta(n^{d_{i}})$$

$$\lim_{n \to \infty} \frac{f(n) + g(n)}{g(n)} = 1 \text{ (if } f(n) = O(g(n))) \qquad \longrightarrow f(n) + g(n) = \Theta(g(n))$$

$$\lim_{n \to \infty} \frac{h(n) \cdot f(n)}{h(n) \cdot g(n)} = 0 \text{ (if } f(n) = O(g(n))) \qquad \longrightarrow h(n) \cdot f(n) = O(h(n) \cdot g(n))$$

## Is Contains a good algorithm?

Contains is correct and has a runtime complexity of  $\Theta(|L|)$  — Sounds good to me!

# **Algorithm** LinearSearch(L, v, o):

**Input:** *L* is an *array*, *v* a value,  $0 \le o \le |L|$ .

1: r := o.

/\* invariant: " $o \le r \le |L|$  and  $v \notin L[o, r]$ ", bound function: |L| - r \*/

2: while  $r \neq |L|$  and also  $L[r] \neq v$  do

3: r := r + 1.

4: **return** *r*.

**Result:** return the first offset r,  $o \le r < |L|$ , with L[r] = v or, if no such offset exists, r = |L|.

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Critique: Contains is *too specialized*  $\longrightarrow$ .

We cannot use Contains for anything else than the contains problem!

## Example

- Searching in only part of the list?
- Finding where *v* is in the list?

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## **Algorithm** LSContains(L, v):

1: **return** LinearSearch $(L, v, 0) \neq |L|$ .

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What is the runtime complexity of LinearSearch?

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Assume: L[i] = v and i is the *first* offset after o equivalent to v. The runtime complexity of LinearSearch is  $\Theta(i-o)$ .

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