

# Week 7 Induction, Recursion, Big-Oh Notation

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Fibonacci Numbers:

$$\text{FIB}(1) = 1$$

$$\text{FIB}(2) = 1$$

$$\text{FIB}(n) = \text{FIB}(n - 1) + \text{FIB}(n - 2) \quad \text{for all } n > 2$$

FIB(1)	1
FIB(2)	1
FIB(3)	2
FIB(4)	3

FIB(5)	5
FIB(6)	8
FIB(7)	13
FIB(8)	21

FIB(9)	34
FIB(10)	55
FIB(11)	89
FIB(12)	144

**Claim:** Every 4th Fibonacci number is divisible by 3.

The corresponding principle of Mathematical Induction on  $\mathbb{N}$ :

**Base Case [B]:**  $P(0)$

**Inductive Step [I]:**  $\forall k \geq 0 (P(k) \Rightarrow P(k + 1))$

**Conclusion:**  $\forall n \in \mathbb{N} P(n)$

## Induction From $m$ Upwards

If

[B]  $P(m)$

[I]  $\forall k \geq m (P(k) \Rightarrow P(k + 1))$

then

[C]  $\forall n \geq m (P(n))$

## Induction Steps $\ell > 1$

If

[B]  $P(m)$

[I]  $P(k) \Rightarrow P(k + \ell)$  for all  $k \geq m$

then

[C]  $P(n)$  for every  $\ell$ 'th  $n \geq m$

## Strong Induction

This is a version in which the inductive hypothesis is stronger.  
Rather than using the fact that  $P(k)$  holds for a single value, we use *all* values up to  $k$ .

If

[B]  $P(m)$

[I]  $[P(m) \wedge P(m+1) \wedge \dots \wedge P(k)] \Rightarrow P(k+1)$  for all  $k \geq m$

then

[C]  $P(n)$ , for all  $n \geq m$

## Forward-Backward Induction

### Idea

To prove  $P(n)$  for all  $n \geq k_0$

- verify  $P(k_0)$
- prove  $P(k_i)$  for infinitely many  $k_0 < k_1 < k_2 < k_3 < \dots$
- fill the gaps

$$P(k_1) \Rightarrow P(k_1 - 1) \Rightarrow P(k_1 - 2) \Rightarrow \dots \Rightarrow P(k_0 + 1)$$

$$P(k_2) \Rightarrow P(k_2 - 1) \Rightarrow P(k_2 - 2) \Rightarrow \dots \Rightarrow P(k_1 + 1)$$

.....

### NB

This form of induction is extremely important for the analysis of algorithms.

## Infinite Descent

To prove that  $Q(n)$ , for all  $n \geq m$ , show

- $\neg Q(n) \Rightarrow \neg Q(n')$  for some  $n' < n$
- there cannot be arbitrarily small  $n$  s.t.  $Q(n)$  is false;  
in particular the “base case”  $Q(m)$  is true

### Structural Induction

The basic approach is always the same — we need to verify that

- [I] for any given object, if the property in question holds for all its predecessors ('smaller' objects) then it holds for the object itself
- [B] the property holds for all minimal objects — objects that have no predecessors; they are usually very simple objects allowing immediate verification

E.g. Induction on Rooted trees

### Recursive Definitions

They comprise basis (B) and recursive process (R).

## Recursive data types

Formal definition of  $\mathbb{N}$ :

- (B)  $0 \in \mathbb{N}$
- (R) If  $n \in \mathbb{N}$  then  $(n + 1) \in \mathbb{N}$

Formal definition of  $\Sigma^*$ :

- (B)  $\lambda \in \Sigma^*$
- (R) If  $w \in \Sigma^*$  then  $aw \in \Sigma^*$  for all  $a \in \Sigma$

w 单词，加一个a 字母

递归可以定义不同的数据类型也可以定义一个函数

## Recursion Definition

Formal definition of concatenation:

- (concat.B)  $\lambda v = v$
- (concat.I)  $(aw)v = a(wv)$

Formal definition of length:

- (length.B)  $\text{length}(\lambda) = 0$
- (length.I)  $\text{length}(aw) = 1 + \text{length}(w)$

## Correctness of Recursive Definitions

A recurrence formula is correct if the computation of any later term can be reduced to the initial values given in (B).

### Example (Incorrect definition)

- Function  $g(n)$  is defined recursively by

$$g(n) = g(g(n - 1) - 1) + 1, \quad g(0) = 2.$$

The definition of  $g(n)$  is incomplete — the recursion may not terminate:

Attempt to compute  $g(1)$  gives

$$g(1) = g(g(0) - 1) + 1 = g(1) + 1 = \dots = g(1) + 1 + 1 + 1 \dots$$

When implemented, it leads to an overflow; most static analyses cannot detect this kind of ill-defined recursion.

However, the definition could be repaired. For example, we can add the specification specify  $g(1) = 2$ .

$$\text{Then } g(2) = g(2 - 1) + 1 = 3,$$

$$g(3) = g(g(2) - 1) + 1 = g(3 - 1) + 1 = 4,$$

...

In fact, by induction ...  $g(n) = n + 1$

This illustrates a very important principle: the boundary (limiting) cases of the definition are evaluated *before* applying the recursive construction.

## Big O

How to describe the time complexity of an algorithm ?

$$T(n) = O(f(n))$$

## Asymptotic Upper Bounds

### Example

MatrixMultiply( $A, B$ ):

**Input** matrices  $A[1..n, 1..n], B[1..n, 1..n]$

```
for i = 1 ... n do
    for k = 1 ... n do
        C[i,k] = 0.0
        for j = 1 ... n do
            C[i,k] = C[i,k] + A[i,j]*B[j,k]
```

Cost = no. of floating point operations and assignments  
 $= n^2 + 3n^3$  (why?)

### Example

Consider two algorithms, one with running time  $f_1(n) = \frac{1}{10}n^2$ , the other with running time  $f_2 = 10n \log n$  (measured in milliseconds).

Input size	$f_1(n)$	$f_2(n)$
100	0.01s	2s
1000	1s	30s
10000	1m40s	6m40s
100000	2h47m	1h23m
1000000	11d14h	16h40h
10000000	3y3m	8d2h

$$f(n) = 20n^2 + 2n \log(n) + (n - 100) \log(n)^2 + \frac{1}{2^n} \log(\log(n))$$

The main contribution to the value of the function for “large” input sizes  $n$  is the term of the *highest order*:

$$20n^2$$

## “Big-Oh” Asymptotic Upper Bounds

### Definition

Let  $f, g : \mathbb{N} \rightarrow \mathbb{R}$ . We say that  $g$  is *asymptotically less than*  $f$  (or:  $f$  is an **upper bound** of  $g$ ) if there exists  $n_0 \in \mathbb{N}$  and a real constant  $c > 0$  such that for all  $n \geq n_0$ ,

$$g(n) \leq c \cdot f(n)$$

Write  $\mathcal{O}(f(n))$  for the class of all functions  $g$  that are asymptotically less than  $f$ .

## Big O

Complexity	Description
1	Execution time does not depend on the input size
$\log(n)$	Very slow increase in running time as $n$ increases
	Whenever $n$ doubles, the running time increases by a constant
$n$	Linear algorithms are optimal if you need to process $n$ inputs
	Whenever $n$ doubles, then so does the running time
$n \log(n)$	Like linear algorithms, 'linearithmic' algorithms scale to huge problems
	Whenever $n$ doubles, the running time more (but not much more) than doubles
$n^2$	Quadratic algorithms are practical on relatively small problems
	Whenever $n$ doubles, the running time increases fourfold
$n^3$	Cubic algorithms are practical on only small problems
	Whenever $n$ doubles, the running time increases eightfold
$2^n$	Exponential algorithms are generally not practical
	Whenever $n$ doubles, the running time squares!
$n!$	Factorial algorithms are very bad in general to compute

$$\frac{1}{10}n^2 \in \mathcal{O}(n^2) \quad 10n \log n \in \mathcal{O}(n \log n) \quad \mathcal{O}(n \log n) \subsetneq \mathcal{O}(n^2)$$

- All logarithms  $\log_b x$
- Exponentials  $r^n$   $\mathcal{O}(\log r^n) \subseteq \mathcal{O}(n^k) \subseteq \mathcal{O}(t^n)$
- Similarly for polynomials

Basic math needed for complexity analysis:

- Logarithms

$$\log_b(xy) = \log_b x + \log_b y, \log_b\left(\frac{x}{y}\right) = \log_b x - \log_b y,$$

$$\log_b x^a = a \log_b x, \log_b a = \frac{\log_x a}{\log_x b}$$

- Exponentials

$$a^{b+c} = a^b a^c, a^{bc} = (a^b)^c, \frac{a^b}{a^c} = a^{b-c}, \sqrt[c]{a^b} = a^{\frac{b}{c}}, b = a^{\log_a b}$$

## “Big-Theta” Notation

### Definition

Two functions  $f, g$  have the *same order of growth* if they scale up in the same way:

There exists  $n_0 \in \mathbb{N}$  and real constants  $c > 0, d > 0$  such that for all  $n \geq n_0$ ,

$$c \cdot f(n) \leq g(n) \leq d \cdot f(n)$$

Write  $\Theta(f(n))$  for the class of all functions  $g$  that have the same order of growth as  $f$ .

Observe that, somewhat symmetrically

$$g \in \Theta(f) \iff f \in \Theta(g)$$

We obviously have

$$\Theta(f(n)) \subseteq \mathcal{O}(f(n))$$

At the same time the ‘Big-Oh’ is *not* a symmetric relation

$$g \in \mathcal{O}(f) \not\Rightarrow f \in \mathcal{O}(g)$$

## Algorithms Analysing

Consider the following recursive algorithm for sorting a list. We take the cost to be the number of list element comparison operations.

Let  $T(n)$  denote the total cost of running `InsSort( $L$ )`

`InsSort( $L$ ):`

**Input** list  $L[0..n - 1]$  containing  $n$  elements

```
if  $n \leq 1$  then return  $L$                       cost = 0
let  $L_1 = \text{InsSort}(L[0..n - 2])$            cost =  $T(n - 1)$ 
let  $L_2 = \text{result of inserting element } L[n - 1] \text{ into } L_1 \text{ (sorted!)}$ 
      in the appropriate place                  cost  $\leq n - 1$ 
return  $L_2$ 
```

$$T(n) = T(n - 1) + n - 1 \quad T(1) = 0$$

## A Divide-and-Conquer Algorithm: Merge Sort

`MergeSort( $L$ ):`

**Input** list  $L$  of  $n$  elements

```
if  $n \leq 1$  then return  $L$                       cost = 0
let  $L_1 = \text{MergeSort}(L[0 .. \lceil \frac{n}{2} \rceil - 1])$     cost =  $T(\frac{n}{2})$ 
let  $L_2 = \text{MergeSort}(L[\lceil \frac{n}{2} \rceil .. n - 1])$     cost =  $T(\frac{n}{2})$ 
merge  $L_1$  and  $L_2$  into a sorted list  $L_3$           cost  $\leq n - 1$ 
      by repeatedly extracting the least element from  $L_1$  or  $L_2$ 
      (both are sorted!) and placing in  $L_3$ 
return  $L_3$ 
```

## A Divide-and-Conquer Algorithm: Merge Sort

MergeSort( $L$ ):

**Input** list  $L$  of  $n$  elements

```
if  $n \leq 1$  then return  $L$                                 cost = 0
let  $L_1 = \text{MergeSort}(L[0.. \lceil \frac{n}{2} \rceil - 1])$           cost =  $T(\frac{n}{2})$ 
let  $L_2 = \text{MergeSort}(L[\lceil \frac{n}{2} \rceil .. n - 1])$         cost =  $T(\frac{n}{2})$ 
merge  $L_1$  and  $L_2$  into a sorted list  $L_3$                   cost  $\leq n - 1$ 
    by repeatedly extracting the least element from  $L_1$  or  $L_2$ 
    (both are sorted!) and placing in  $L_3$ 
return  $L_3$ 
```

Let  $T(n)$  be the number of comparison operations required by MergeSort( $L$ ) on a list  $L$  of length  $n$

$$T(n) = 2T\left(\frac{n}{2}\right) + (n - 1) \quad T(1) = 0$$

## Master Theorem

- (case 1)  $T(n) = T(n - 1) + bn^k$   
solution  $T(n) = \mathcal{O}(n^{k+1})$
- (case 2)  $T(n) = cT(n - 1) + bn^k$ ,  $c > 1$ :  
solution  $T(n) = \mathcal{O}(c^n)$

The following cases cover many divide-and-conquer recurrences that arise in practice:

$$T(n) = d^\alpha \cdot T\left(\frac{n}{d}\right) + \mathcal{O}(n^\beta)$$

- (case 1)  $\alpha > \beta$   
solution  $T(n) = \mathcal{O}(n^\alpha)$
- (case 2)  $\alpha = \beta$   
solution  $T(n) = \mathcal{O}(n^\alpha \log n)$
- (case 3)  $\alpha < \beta$   
solution  $T(n) = \mathcal{O}(n^\beta)$

### Exercise

## Exercise

Consider an **increasing** function  $f : \mathbb{N} \rightarrow \mathbb{N}$

i.e.,  $\forall m, n (m \leq n \Rightarrow f(m) \leq f(n))$

and a function  $g : \mathbb{N} \rightarrow \mathbb{N}$  such that

- $f(0) < g(0)$
- $f(1) = g(1)$
- if  $f(k) \geq g(k)$  then  $f(k+1) \geq g(k+1)$ , for all  $k \in \mathbb{N}$

Always true, false or could be either?

- (a)  $f(n) > g(n)$  for all  $n \geq 1$  — false  
(b)  $f(n) > g(n)$  for some  $n \geq 1$  — could be either  
(c)  $f(n) \geq g(n)$  for all  $n \geq 1$  — true  
(d)  $g$  is decreasing ( $m \leq n \Rightarrow g(m) \geq g(n)$ ) — could be e

## Example

**Theorem.** For all  $n \geq 1$ , the number  $8^n - 2^n$  is divisible by 6.

Induction proof:

## Example

$$\begin{aligned}\text{FIB}(1) &= \text{FIB}(2) = 1 \\ \text{FIB}(n) &= \text{FIB}(n-1) + \text{FIB}(n-2)\end{aligned}$$

Every 4th Fibonacci number is divisible by 3.

Induction proof:

## Example

**Claim:** All integers  $\geq 2$  can be written as a product of primes.

[B] 2 is a product of primes

[I] If all  $x$  with  $2 \leq x \leq k$  can be written as a product of primes, then  $k+1$  can be written as a product of primes, for all  $k \geq 2$

### Example

Binary search in an (ordered) list of  $n - 1$  elements requires no more than  $\lceil \log_2 n \rceil$  comparisons.

### Example

For a planar, connected graph let  $F$  be the number of faces (enclosures) including the exterior face,  $E$  the number of edges, and  $V$  the number of vertices.

**Euler's formula:** 
$$V - E + F = 2 \quad (\text{EF})$$

## Example: Induction on Rooted Trees

We write  $T = \langle r; T_1, T_2, \dots, T_k \rangle$  for a tree  $T$  with root  $r$  and  $k$  subtrees at the root  $T_1, \dots, T_k$

If

- [B]  $p(\langle v; \rangle)$  for trees with only a root
- [I]  $p(T_1) \wedge \dots \wedge p(T_k) \Rightarrow p(T)$  for all trees

$$T = \langle r; T_1, T_2, \dots, T_k \rangle$$

then

- [C]  $p(T)$  for every tree  $T$

### Theorem

In any rooted tree the number of vertices is one more than the number of edges.

### Proof.

### Exercise

4.4.4 (a) Give a recursive definition for the sequence

$$(2, 4, 16, 256, \dots)$$

To generate  $a_n = 2^{2^n}$  use  $a_n = (a_{n-1})^2$ .

(The related "Fermat numbers"  $F_n = 2^{2^n} + 1$  are used in cryptography.)

(b) Give a recursive definition for the sequence

$$(2, 4, 16, 65536, \dots)$$

To generate a "stack" of  $n$  2's use  $b_n = 2^{b_{n-1}}$ .

(These are *Ackermann's numbers*, first used in logic. The function is extremely slow growing; it is important for the analysis of several data organisation algorithms.)

4.4.2 Define  $s_1 = 1$  and  $s_{n+1} = \frac{1}{1+s_n}$  for  $n \geq 1$

Then  $s_1 = 1, s_2 = \frac{1}{2}, s_3 = \frac{2}{3}, s_4 = \frac{3}{5}, s_5 = \frac{5}{8}, \dots$

Nominators/denominators remind one of the Fibonacci sequence.

Prove by induction that

$$s_n = \frac{\text{FIB}(n)}{\text{FIB}(n+1)}$$

用数学归纳法证明  $S_n$  成立

**4.3.5** True or false?

- (a)  $2^{n+1} = \mathcal{O}(2^n)$
- (b)  $(n + 1)^2 = \mathcal{O}(n^2)$
- (c)  $2^{2n} = \mathcal{O}(2^n)$
- (d)  $(200n)^2 = \mathcal{O}(n^2)$

**4.3.6** True or false?

- (b)  $\log(n^{73}) = \mathcal{O}(\log n)$
- (c)  $\log n^n = \mathcal{O}(\log n)$
- (d)  $(\sqrt{n} + 1)^4 = \mathcal{O}(n^2)$

**4.3.22** The following algorithm raises a number  $a$  to a power  $n$ .

```

 $p = 1$ 
 $i = n$ 
while  $i > 0$  do
     $p = p * a$ 
     $i = i - 1$ 
end while
return  $p$ 

```

Determine the complexity (no. of comparisons and arithmetic ops).

**4.3.21** The following algorithm gives a fast method for raising a number  $a$  to a power  $n$ .

```

 $p = 1$ 
 $q = a$ 
 $i = n$ 
while  $i > 0$  do
    if  $i$  is odd then
         $p = p * q$ 
     $q = q * q$ 
     $i = \lfloor \frac{i}{2} \rfloor$ 
end while
return  $p$ 

```

Determine the complexity (no. of comparisons and arithmetic ops).

Big O exercises

$$T(n) = T\left(\frac{n}{2}\right) + n^2, \quad T(1) = a$$

Mergesort has

$$T(n) = 2T\left(\frac{n}{2}\right) + (n - 1)$$

recurrence for the number of comparisons.

Beyond the Master Theorem

Solve  $T(n) = 3^n T\left(\frac{n}{2}\right)$  with  $T(1) = 1$

Let  $n \geq 2$  be a power of 2 then