



Artificial Intelligence Paradigm

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Lecture 2

Outline



- 1 Recursion
- 2 Divide-and-Conquer
 - Paradigm
 - Example
- 3 Dynamic programming
 - Paradigm
 - Characteristics
 - Example

Overview



A recursive function **calls itself** *directly* or *indirectly*.

It is a programming tool, based on a non-intuitive mode of thinking.

Recursion form the base to another paradigm:
DIVIDE-AND-CONQUER.

Overview

ITERATION:

- **Uses** repetition structures (*for, while or do...while*)
- **Repetition through** explicitly use of repetition structure
- **Terminates when** loop-continuation conditions fail
- **Controls repetition** by using a counter.

RECURSION:

- **Uses** selection structures (*if, if...else or switch*)
- **Repetition through** repeated method calls
- **Terminates when** base cases are satisfied
- **Controls repetition** by dividing problem into simpler one.

Stack



To understand how recursion works, it helps to visualize what's going on. To help visualize, we will use a common concept called the STACK.

Stack

A stack basically operates like a container with priority on inside objects.

It has only two operations:

- PUSH: you can push something onto the stack.
- POP: you can pop something off the top of the stack.

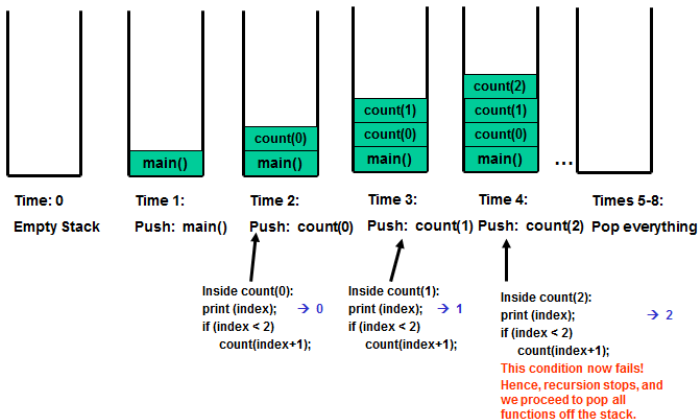
Stacks and Methods

When you run a program, the computer creates a stack for you.

- Each time you **invoke** a method, the method is placed on top of the stack (PUSH).
- When the method **returns** or exits, the method is popped off the stack (POP).
- If a method calls itself recursively, you just push another copy of the method onto the stack.

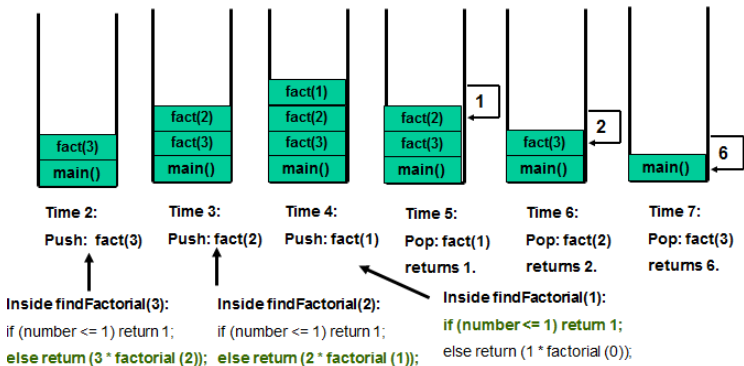
Example

Consider *Void Count(int index)* a recursion function: *if(index < 2)*
Count(index+1)



Another Example

Consider *Int Factorial(int number)* a recursion function: if ($number == 1$) || ($number == 0$) return 1; else return ($number * Factorial(number-1)$)



Pro. and Con.

- 1 More overhead than iteration;
- 2 More memory intensive than iteration;
- 3 Can also be solved iteratively;
- 4 Often can be implemented with only a few lines of code.

Introduction

DIVIDE-AND-CONQUER is not a trick. It is a very useful general purpose tool for designing efficient algorithms.

It follows those steps:

- 1 Divide:** *divide a given problem into subproblems (of approximately equal size)*
- 2 Conquer:** *solve each subproblem directly or recursively*
- 3 Combine:** *and combine the solutions of the subproblems into a global solution.*

Algorithm

The *general structure* of an algorithm designed by using divide and conquer is:

```
divide_and_conquer( $P(n)$ )  
if  $n \leq n_c$  then  $\langle$  solve directly  $P(n)$   $\rangle$   
else  
   $\langle$  divide  $P(n)$  in  $k$  subproblems  $P_1(n_1), \dots, P_k(n_k)$   $\rangle$   
  for  $i \leftarrow 1, k$   
    divide_and_conquer( $P_i(n_i)$ )  
  endfor    $\langle$  combine the results  $\rangle$   
endif
```

Mergesort

The algorithm sorts an array of size N by splitting it into two parts of almost equal size, recursively sorting each of them, and then merging the two sorted subarrays back together into a fully sorted list in $O(N)$ time (comparing in order both array into a single array).

Mergesort(A, i, j) : Sort $A[i \dots j]$

if ($i \neq j$)

{ Mergesort ($A, i, \lfloor \frac{i+j}{2} \rfloor$)

Mergesort ($A, 1 + \lfloor \frac{i+j}{2} \rfloor, j$)

Merge the two sorted lists

$A[i \dots \lfloor \frac{i+j}{2} \rfloor]$ and $A[1 + \lfloor \frac{i+j}{2} \rfloor, j]$
and return complete sorted list

}

Complexity

$$M\left(\frac{j-i}{2}\right)$$

$$M\left(\frac{j-i}{2}\right)$$

$$O(j-i)$$

Mergesort

The algorithm sorts an array of size N by splitting it into two parts of almost equal size, recursively sorting each of them, and then merging the two sorted subarrays back together into a fully sorted list in $O(N)$ time.

The running time of the algorithm satisfies the Master theorem:

$$\forall N > 1, M(N) \leq 2M(N/2) + O(N)$$

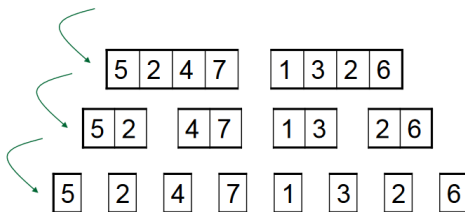
wich we implies

$$M(N) = O(N \log N).$$

Mergesort

Divide

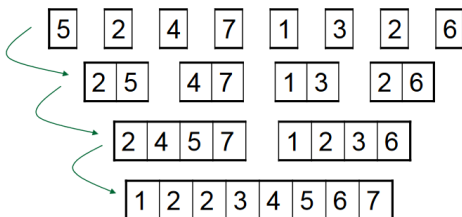
$\log(n)$ divisions to split an array of size n into elements.



Mergesort

Conquer

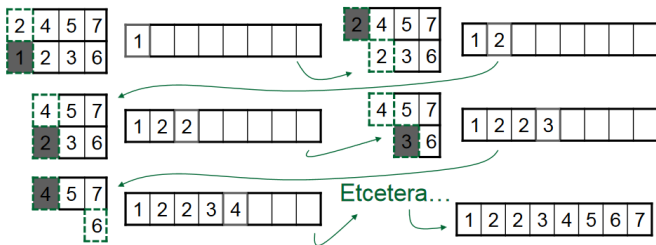
$\log(n)$ iterations, each iterations takes $O(n)$ time, for a total time $O(n \log n)$



Mergesort

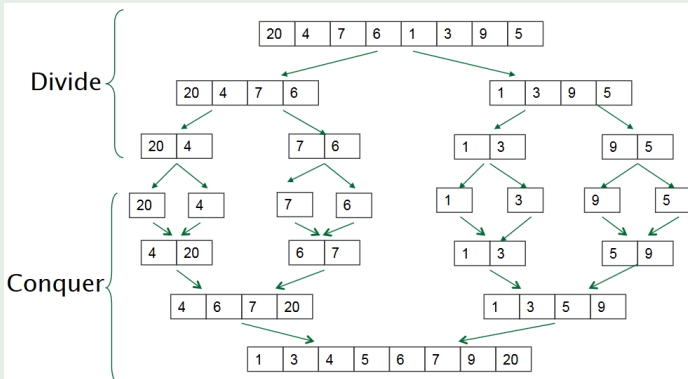
Combine

Two sorted arrays can be merged in linear time into a sorted array.



Mergesort

Example



Overview

DYNAMIC PROGRAMMING is a powerful algorithmic design technique. Large class of seemingly exponential problems have a polynomial solution via dynamic programming, particularly for optimization problems.

The main difference between greedy, D&C and DP programs are:

- **Greedy:** *build up a solution incrementally, optimizing some local criterion.*
- **Divide-&-conquer:** *break up a problem into independent subproblems, solve each one and combine solution.*
- **Dynamic programming:** *break up a problem into a series of overlapping subproblems, and build up solutions to larger and larger subproblems.*

Four steps of Dynamic programming

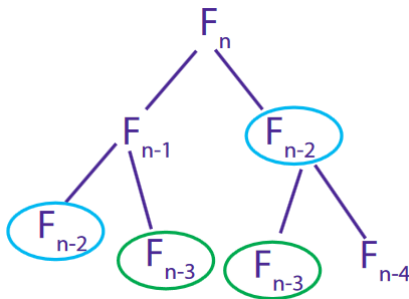
- 1 Define subproblems and characterize the structure of an optimal solution (OPTIMAL SUBSTRUCTURE).
- 2 Recursively define the value of an optimal solution (RECURSIVE FORMULATION).
- 3 TOP-DOWN: Recurse and memoize; or BOTTOM-UP: Compute the value of an optimal solution using an array/table.
- 4 Construct an OPTIMAL SOLUTION from the computed information.

Example

$\text{Fib}(n)$: if $n \leq 2$ return 1; else return $\text{Fib}(n-1) + \text{Fib}(n-2)$;

Running time: $M(n) = M(n-1) + M(n-2) + O(1) \geq 2M(n-2) + O(1) \geq 2^{n/2}$.

An exponential running time is bad for this kind of problem. We could memoize some inner solution to compute the problem.



Top-Down Dynamic Program

```
memo = { }  
fib(n):  
    if n in memo: return memo[n]  
    else: if n ≤ 2 : f = 1  
          else: f = fib(n - 1) + fib(n - 2)  
          memo[n] = f  
          return f
```

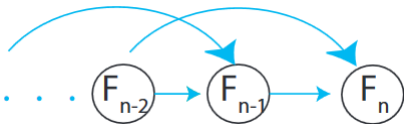
In this program, fib(k) only recurses first time called, for any k . Thus, there are only n nonmemoized calls. Each memoized calls are free, in $O(1)$. Top-Down memoize and re-use solutions to subproblems that help solve problem.

Bottom-Up Dynamic Program

```
fib = {}  
for  $k$  in  $[1, 2, \dots, n]$ :  
    if  $k \leq 2$ :  $f = 1$   
    else:  $f = \text{fib}[k - 1] + \text{fib}[k - 2]$   
     $\text{fib}[k] = f$   
return  $\text{fib}[n]$ 
```

$\left. \begin{array}{l} \left. \begin{array}{l} \left. \begin{array}{l} \text{fib} = \{\} \\ \text{for } k \text{ in } [1, 2, \dots, n]: \\ \text{if } k \leq 2: f = 1 \\ \text{else: } f = \text{fib}[k - 1] + \text{fib}[k - 2] \\ \text{fib}[k] = f \end{array} \right\} \theta(1) \end{array} \right\} \theta(n) \end{array} \right\}$

Bottom-up dynamic program construct the solution from the last subproblems to the problem itself. We have just to remember the last two fibs. Bottom-up dynamic programs follow the same scheme.



Optimal Substructure

Definition

A problem have OPTIMAL SUBSTRUCTURE when the optimal solution of a *problem contains in itself solutions for subproblems of the same type.*

If a problem presents this characteristic, we say that it respects the optimality principle.

Overlapping Substructure

Definition

A problem is said to have OVERLAPPING SUBPROBLEMS if the *problem can be broken down into subproblems which are reused several times or a recursive algorithm for the problem solves the same subproblem over and over* rather than always generating new subproblems (for example by memoization).

See Fibonacci example.

Four steps of Dynamic programming v2

- 1 Characterize the optimal solution of the problem.
 - 1 Understand the problem
 - 2 Verify if a brute force algorithm is enough (optional)
 - 3 Generalize the problem
 - 4 Divide the problem in subproblems of the same type
 - 5 Verify if the problems obeys the optimality principle and overlapping subproblems.If the problem presents these two characteristics, we know that dynamic programming is applicable.

Four steps of Dynamic programming v2

- 2 Recursively define the optimal solution, by using optimal solutions of subproblems
 - 1 Recursively define the optimal solution value, exactly and with rigour, from the solutions of subproblems of the same type
 - 2 Imagine that the values of optimal solutions are already available when we need them
 - 3 Mathematically define the recursion

Four steps of Dynamic programming v2

- 3 Compute the solutions of all subproblems: top-down
 - 1 Use the recursive function directly obtained from the definition of the solution and keep a table with the results already computed
 - 2 When we need to access a value for the first time we need to compute it, and from then on we just need to see the already computed result.

Four steps of Dynamic programming v2

- 3 Compute the solutions of all subproblems: bottom-up
 - 1 Find the order in which the subproblems are needed, from the smaller subproblem until we reach the global problem and implement, using a table
 - 2 Usually this order is the inverse to the normal order of the recursive function that solves the problem

Four steps of Dynamic programming v2

- 4 Reconstruct the optimal solution, based on the computed values
 - 1 Directly from the subproblems table
 - 2 OR New table that stores the decisions in each step

Matches

- There are n matches
- In each play you can choose to remove 1, 3, or 8 matches
- Whoever removes the last stones, wins the game.

GIVEN THE NUMBER OF INITIAL STONES, CAN THE PLAYER THAT STARTS TO PLAY GUARANTEE A WIN?

Matches

- 1 Characterize the optimal solution of the problem.
 - In BRUTE FORCE algorithm, there are 3^k possible games.
 - Let $win(i)$ be a boolean value representing if we can win when there are i matches:
 - $win(1), win(3), win(8)$ are true
 - For the other cases:
 - if your play goes make the game go to winning position, then our opponent can force your defeat.
 - Therefore, our position is a winning position if we can get to a losing position.
 - If all possible movements lead to a winning position, then your position is a losing one.

Matches

2 Recursively define the optimal solution.

■ $win(0) = false$

■ $win(i) = \begin{cases} true & \text{if } (win(i-1) = false \parallel win(i-3) = false \parallel win(i-8) = false) \\ false & \text{otherwise} \end{cases}$

Matches

3 Compute the solutions of all subproblems: bottom-up

- For $i \leftarrow 0$ to n do
 - if $((i \geq 1 \ \&\& \text{win}(i-1) = \text{false}) \ || \ (i \geq 3 \ \&\& \text{win}(i-3) = \text{false}) \ || \ (i \geq 8 \ \&\& \text{win}(i-8) = \text{false}))$
 - then $\text{win}(i) \leftarrow \text{true}$
 - else $\text{win}(i) \leftarrow \text{false}$

i	0	1	2	3	4	5	6	7	8	9	10	11	12
win(i)	f	t	f	t	f	t	f	t	t	t	t	f	t

Fundamental knowledge

YOU HAVE TO KNOW BEFORE THE TUTORIAL:

1 *Recursion:*

- 1** *Principle;*
- 2** *Stack: how it works;*
- 3** *Divide-and-Conquer paradigm: three steps and general structure;*
- 4** *Understand the mergesort algorithm.*

2 *Dynamic programming:*

- 1** *Principle;*
- 2** *Dynamic programming paradigm: four steps and bottom-up recursion (see v2);*
- 3** *Optimal substructure;*
- 4** *Overlapping subproblems.*