



DYNAMIC PROGRAMMING, PART 1: INTRODUCTION AND EXAMPLES

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CMP 601 – Algorithms and Theory of Computation —

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Outline

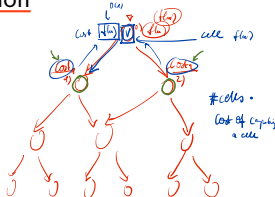
1. Introduction
2. Toy example: Fibonacci
3. Subset sum problem
4. Knapsack problem

$$A(x) = \sum_{0 \leq i \leq n} a_i x^i$$

Ex. $A(x_0), A(x_1), \dots, A(x_{n-1})$
 $x_0, \dots, x_{n-1}$ $a_0, \dots, a_{n-1}$



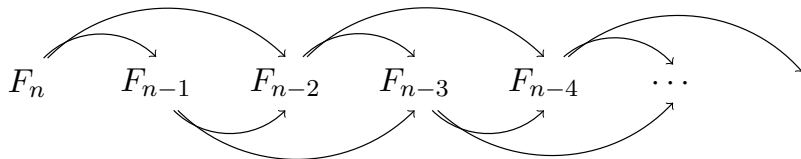
- A recursive definition
 - So: problem is solved via subproblems
- A large overlap, such that caching makes sense
- Complexity then: size of the cache times time to fill each cell
- Optimal substructure: *↳ memory req. / space complexity*
 - For decision problems: subproblems cover all cases
 - For optimization problems: one of the subproblems can be extended to the optimal solution



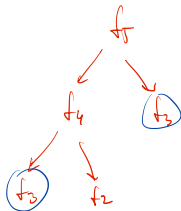
Definition


$$F_n = \begin{cases} F_{n-1} + F_{n-2}, & \text{caso } n \geq 2, \\ 1, & \text{caso } n \in \{0, 1\}. \end{cases}$$

F_n	1	1	2	3	5	8	13
n	0	1	2	3	4	5	6



```
fib(n) :=  
  if  $n \leq 1$  then  
    return 1  
  else  
    return fib(n - 1) + fib(n - 2)  
  end if  
end
```



$f_0 := 1$
 $f_1 := 1$
 $f_i := \perp$ para $i \geq 2$

Memoization

$\text{fib}(n) :=$
 if $f_n \neq \perp$ then
 $f_n := \text{fib}(n-1) + \text{fib}(n-2)$
 end if
 return f_n
 end

cost per cell $\cdot$ # cells = n

$\Rightarrow O(n)$.

time / space.

f_{n-1}

f_{n-2}

2

TOY EXAMPLE: FIBONACCI

Cache evolution

DYNAMIC PROGRAMMING,
PART 1: INTRODUCTION
AND EXAMPLES

	f_5	f_4	f_3	f_2	f_1	f_0
Initial	⊥	⊥	⊥	⊕	⊕	⊕
1	⊥	⊥	⊥	⊕	⊕	⊕
2	⊥	⊥	⊕	⊕	⊕	⊕
3	⊥	⊕	⊕	⊕	⊕	⊕
4	⊕	⊕	⊕	⊕	⊕	⊕

Sequential implementation

```
fib(n) :=  
  f0 := 1  
  f1 := 1  
  for i ∈ [2, n] do  
    fi := fi-1 + fi-2  
  end for  
  return fn  
end
```

$f_i = F_i$

$f_i := f_{i-1} + f_{i-2}$

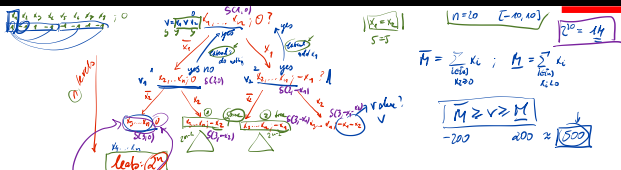
```
fib(n) :=  
2 (f := 1  
   g := 1  
   for i ∈ [2, n] do  
     { invariante:  $f = F_{i-2} \wedge g = F_{i-1}$  }  
     g := f + g  
     f := g - f  
     { invariante:  $f = F_{i-1} \wedge g = F_i$  }  
   end for
```

Space: $O(1)$
Time: $O(n)$

$$X = \sum_{i \in [n]} x_i / 2$$

$$x_i \in \mathbb{Z}$$

- Given numbers $x_1, x_2, \dots, x_n$ is there a non-empty subset whose sum is 0? $\checkmark$, $\underline{\underline{X}}$
- Problem is NP-hard.
- Brute-force algorithm: test all subsets in $O(2^n n)$.



- Subproblems: either x_1 is part of the solution, or it is not
 - If it isn't: find a subset of $x_2, \dots, x_n$ that sums to 0 $\leftarrow$
 - If it is: find a subset of $x_2, \dots, x_n$ that sums to $-x_1$.
 - We can see: a subproblem consists of
 - a suffix of the elements $x_i, x_{i+1}, \dots, x_n$
 - and a target value v
- Handwritten notes:* $n=20$, 2^1 , $1500 \approx 1000$

- So we define: $S(i, v)$: there is a non-empty subset of $x_i, x_{i+1}, \dots, x_n$ summing to v
- And we want to know: $S(1, 0)$.
- Recursive definition:

$$S(i, v) = \begin{cases} S(i+1, v) \vee S(i+1, v - x_i), & 1 \leq i < n, \\ x_n = v, \text{ true} & i = n, \end{cases}$$

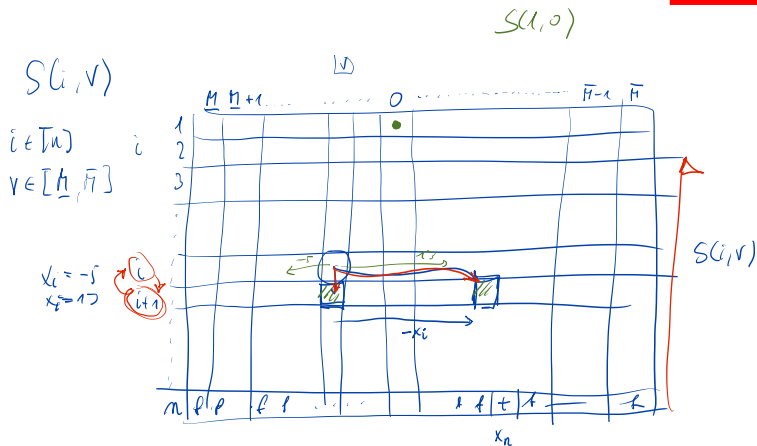
$0 \leq i \leq n-1$ in $S(n, r)$. Subset of $\{n\}$ sum to r ?

- Now we can apply all the same steps as for the Fibonacci example $M = A - M$
- Complexity? $\underbrace{(n+1)}_{\# \text{ cols}} \cdot \underbrace{n}_{\text{entries}} \cdot \underbrace{O(1)}_{\text{cost/entry}} = \underline{O(n^2)}$

3

SUBSET SUM PROBLEM (Empty)

DYNAMIC PROGRAMMING, PART 1: INTRODUCTION AND EXAMPLES



$$\begin{array}{l|l} \text{adv.} & S(n,v) = [x_n = v], \forall v \\ \text{ret.} & S(i,v) = \perp \quad \forall 1 \leq i < n, \forall v \end{array}$$

```

for i = n-1, n-2, ..., 1
  for v ∈ [1, M] | [1, n-1, ..., M-1, M]
    S(i,v) = S(i+1,v) ∨ S(i+1, v-xi)
return S(1,0)

```

- Given n items with values $v_1, \dots, v_n \geq 0$ and weights $w_1, \dots, w_n \geq 0$ and a maximum weight W
- Find the subset $S \subseteq [n]$ of the largest value $v(S) = \sum_{i \in S} v_i$ that fits into the Knapsack, i.e. $w(S) = \sum_{i \in S} w_i \leq W$

- Same dichotomy as for subset sum.
- If item 1 is not part of the optimal solution: find the optimal solution for $2, \dots, n$ with maximum weight W
- If item 1 is part of the optimal solution: find the optimal solution for $2, \dots, n$ with maximum weight $W - w_1$ and add v_1
- Thus: a subproblem is defined by
 - a suffix of the item $i, i + 1, \dots, n$
 - and a maximum weight w

- So we define: $K(i, w)$: the optimal value using item $i, \dots, n$ with maximum weight w .
- And we want to know: $K(1, W)$.
- Recursive definition:

$$K(i, w) = \begin{cases} \max\{K(i+1, w), K(i+1, w - w_i) + v_i\}, & 1 \leq i \leq n, w_i \leq w \\ K(i+1, w), & 1 \leq i \leq n, w_i > w \\ 0, & i > n. \end{cases}$$

- Now we can apply all the same steps as for the Fibonacci example, again
- Complexity?

4

KNAPSACK PROBLEM (Empty)

DYNAMIC PROGRAMMING,
PART 1: INTRODUCTION
AND EXAMPLES

4

KNAPSACK PROBLEM (Empty)

DYNAMIC PROGRAMMING,
PART 1: INTRODUCTION
AND EXAMPLES