

# Dynamic Programming (DP)

...

Using recursive solution properties to trade compute time with  
memory

# Some thoughts about DP

“Once you understand it, dynamic programming is probably the easiest algorithm design to apply in practice. [...] until you understand dynamic programming, it seems like magic”, S.S. Skiena

# How to solve an optimisation problem ?

Core idea that leads to DP

## Strategy 1 : Exhaustive search (enumeration)

- Guaranteed to find the best solution

→ Global optimality

- Really slow : we have to enumerate all possible combinations

## Strategy 2 : Greedy algorithm (heuristic)

- Based on local optimality with heuristics:

“take the best local decision at each step”

→ No guaranty for global optimality

- Usually efficient

What if we could have everything at once? -> idea behind DP

# What is Dynamic Programming ?

Both:

- **Mathematical Optimization** Method
- Algorithmic **Paradigm**

What it means:

- Link to math: Kind of similar to **Induction Proof** , with the difference that the number of steps to perform is finite
- Principle: solve complicated problems by breaking them down into simpler sub-problems in a recursive manner.

# Informatics vision: Divide & Conquer X Memoization

## Divide & Conquer

- Break down the problem into smaller problems
- Solve the subproblems
- Combine the results

## Memoization

- Identify the redundant subproblems to solve them only once

# A (really) quick reminder on Divide & Conquer

Question: is 9 in this sorted list? 1 2 5 7 8 9 10 12

→ Naive search: look at every element from the start,  $O(n)$

→ Binary search: split the search space in half at each iteration,  $O(\log(n))$

1 2 5 7 8 9 10 12

1 2 5 7 8 9 10 12

1 2 5 7 8 9 10 12

1 2 5 7 8 9 10 12 Found it !

# How to choose the subproblems?

- The idea is to find how to recursively reach the easy problems, without losing optimality
- We want the result of the subproblems to be useful in order to compute the result of the greater one we're struggling with

**Bellman's principle of optimality:** if subproblems' result are optimal then their combination will be too

# Bellman equations

Bellman equations are the rules to go from one subproblem to another.

- They need to go with Bellman's principle of optimality

Try smally decreasing any problem parameter (number of element, size of a line, ...)

The subproblems have to strictly decrease in size, leaning toward the base case

→ There cannot be any cycle !

- Don't forget the base case, The recursion (induction) has to stop at some point !



# DP - Why such a “bad” name ?

The term DP was invented by Richard Bellman in the 1940s - 1950s.

- Originally, DP describes problems related to dynamic processes where finding the optimal solution can be done by taking decision one after the other.

Bellman was working on optimization problems in a setting where funding often required work to **sound mathematically sophisticated yet obscure** to avoid interference from military bureaucracy.

# How Bellman coined the term “Dynamic Programming”

“The 1950s were not good years for mathematical research. We had a very interesting gentleman in Washington named Wilson. He was Secretary of Defense, and he actually had a pathological fear and hatred of the word “research”. [...] What title, what name, could I choose? [...] Let's take a word that has an absolutely precise meaning, namely dynamic, in the classical physical sense. It also [...] impossible to use the word dynamic in a pejorative sense. Try thinking of some combination that will possibly give it a pejorative meaning. It's impossible. Thus, I thought **dynamic programming** was a good name. It was something not even a Congressman could object to. So I used it as an umbrella for my activities.” —Richard Bellman

# Alternative names

- **Memoization-Based Programming:** Highlights the reuse of intermediate results to avoid redundant computation.
- **Subproblem Optimization Programming:** Emphasizes breaking problems into smaller subproblems and solving them optimally.
- **Overlapping Subproblems Method:** Highlights the key feature of DP where subproblems overlap, making memoization or tabulation effective.
- **Iterative Refinement Programming:** Describes the process of incrementally building up solutions in the bottom-up approach.
- **Recursive Optimization Programming:** Combines the recursive nature and optimization focus of DP.

# A common example: the Fibonacci sequence

Rules (Bellman equations) :

$$F(0) = 0, F(1) = 1$$

$$F(n) = F(n - 1) + F(n - 2)$$

How to compute efficiently  $F(n)$   
for a large  $n$ ?



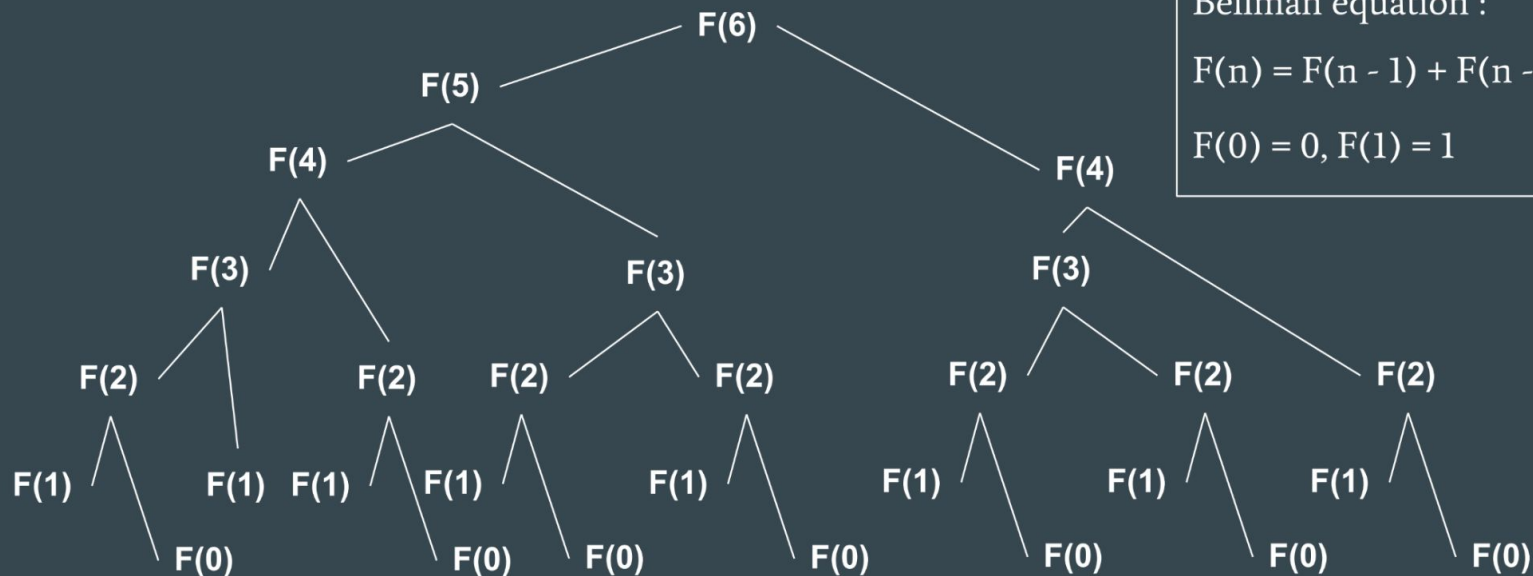
# The Fibonacci sequence

Naive recursive algorithm :

```
def Fibonacci(n):  
    if n == 0:  
        return 0  
    if n == 1:  
        return 1  
    else:  
        return Fibonacci(n - 1) + Fibonacci(n - 2)
```

Fibonacci(n)

# The Fibonacci sequence



Bellman equation :

$$F(n) = F(n - 1) + F(n - 2)$$

$$F(0) = 0, F(1) = 1$$

This algorithm runs in  $O(2^n)$ , there is probably a better way to do this..

# Memoization: how to trade space for time

Keep track of which subproblems have already been solved

- Keep those subproblems' result in memory
- If one shows up again, take its result out of memory instead of computing it again

# An efficient algorithm for computing the Fibonacci sequence

```
def Fibonacci(n):  
    if n == 0:  
        return 0  
    if n == 1:  
        return 1  
    if memo[n] != -1:  
        return memo[n]  
    else:  
        result = Fibonacci(n - 1) + Fibonacci(n - 2)  
        memo[n] = result  
        return result  
  
memo = [-1] * (n + 1)  
Fibonacci(n)
```



# An efficient algorithm for computing the Fibonacci sequence

```
def Fibonacci(n):  
    if n == 0:  
        return 0  
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    if memo[n] != -1:  
        return memo[n]  
    else:  
        result = Fibonacci(n - 1) + Fibonacci(n - 2)  
        memo[n] = result  
        return result
```

```
memo = [-1] * (n + 1)  
Fibonacci(n)
```

<Base case>

<reuse already computed  
subproblems if possible>

<Bellman equations>

<store result (memoize)>

# Sequence of calls with this algorithm



Bellman equation :

$$F(n) = F(n - 1) + F(n - 2)$$

$$F(0) = 0, F(1) = 1$$

First call

Base case

Already computed

We've achieved a  $O(n)$  algorithm !

# Bottom Up vs Top Down

## Bottom up

- Iterative version
- Build subproblems and grow toward the global one
- A bit faster, better for memory concerns



Initial problem

Base cases

## Top down

- Recursive version
- Decrease from the initial problem to the base cases
- Easy to implement once you have the Bellman equation



Initial problem

Base cases

# Bottom Up vs Top Down : Fibonacci sequence

## Bottom Up

```
fibonacci = [0] * (n + 1)
fibonacci[0] = 0
fibonacci[1] = 1
for k in range(2, n + 1):
    fibonacci[k] = fibonacci[k - 1]
                  + fibonacci[k - 2]
```

## Top Down

```
def fibonacci(n):
    if n == 0:
        return 0
    if n == 1:
        return 1
    if memo[n] != -1:
        return memo[n]
    else:
        result = fibonacci(n - 1)
                + fibonacci(n - 2)
        memo[n] = result
        return result
```

```
memo = [-1] * (n + 1)
fibonacci(n)
```

# Quick recap : What do we need ?

- Find a way to split the initial problem into subproblems that are easier to solve
- Find the Bellman equation to jump from one problem to its subproblems easily
- Think about the base cases you can consider !
- Don't forget to memoize
- Enjoy being a wizard of algorithms!

Next lectures :

- How are you going to store the subproblems' results? Choose your data structures wisely !
- Common DP problems
- Take a step back : how to quickly evaluate if DP is necessary / will be fast enough?

# Credits

Slides: Arthur Tondereau, Louis Sugy, Onyr (Florian Rascoussier) for INSAIgo

The algorithm design manual, Steven S. Skiena

Wikipedia of course!