

# THEORY OF DYNAMIC PROGRAMMING

This page intentionally left blank

# Dynamic Programming (DP)

Credits: Erik Demaine

③

- General, powerful algorithmic design technique
- Good for optimization problem
- "Careful brute force"

- Invented by Richard Bellman <sup>in 1953,</sup> an American applied mathematician
- Also known as Bellman equation
- Basic idea: subproblems + "reuse"

## Fibonacci numbers:

$$F_1 = F_2 = 1$$

$$F_n = F_{n-1} + F_{n-2}$$

Goal: Compute  $F_n$

Origin: Sanskrit "chandas", Pingala (200 BC), Virahanka (700 AD)

Ref: "Liber Abaci" 1202, Fibonacci

- (first western book to describe "arabic" numbers) a.k.a "The Book of Calculations" or "The Book of Abacus"

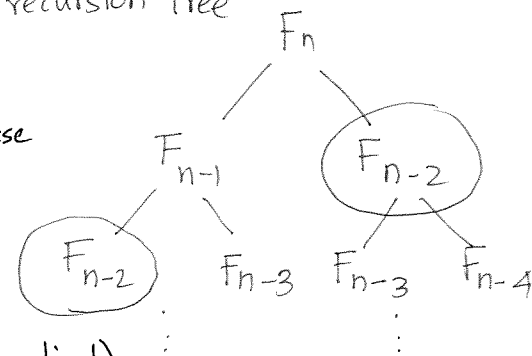
- Growth of an "idealized" rabbit population

## Naïve recursive algorithm:

fib(n):

(\*)  $\begin{cases} \text{if } n \leq 2: f = 1 & // \text{base case} \\ \text{else: } f = \text{fib}(n-1) + \text{fib}(n-2) \\ \text{return } f \end{cases}$

recursion tree



Correct Algorithm, but not efficient (exponential)

$$T(n) = T(n-1) + T(n-2) + \Theta(1)$$

$$\begin{aligned} T(n) &> 2T(n-2) \\ T(n) &= \Theta(2^{n/2}) \end{aligned}$$

## Memoized DP algorithm:

memo: memo pad  
- write down

memo = {}

fib(n):

if n in memo: return memo[n]

(\*)  $\begin{cases} \text{if } n \leq 2: f = 1 & // \text{base case} \\ \text{else: } f = \text{fib}(n-1) + \text{fib}(n-2) \\ \text{memo}[n] = f \\ \text{return } f \end{cases}$

④

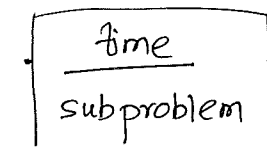
Note :  $\text{fib}(k)$  only recurses the first time it's called.  $\forall k$

- memoized calls are  $\Theta(1)$
  - # of non-memoized calls is  $n$   
 $\text{fib}(1), \text{fib}(2), \dots, \text{fib}(n)$
  - non-recursive work per call =  $\Theta(1)$
- $\Rightarrow \text{time} = \Theta(n)$

DP core idea  $\approx$  recursion + memoization

- memoize (remember)
- & reuse solutions to subproblems that help solve the problem

$\Rightarrow \text{time} = \# \text{ subproblems}$



ignore recursion

Bottom-up DP algorithm

$\text{fib} = \{ \}$

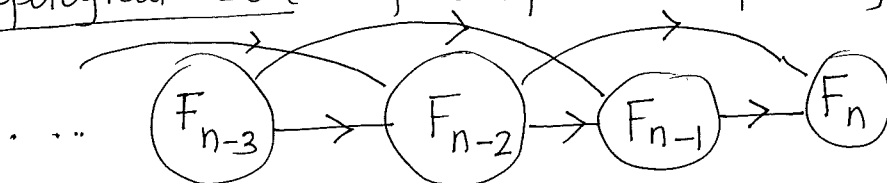
- for  $k$  in range ~~(0, n)~~:  $(1, n+1)$ :

$\otimes$   $\left[ \begin{array}{l} \text{if } k \leq 2: f = 1 \quad // \text{ base case} \\ \text{else: } f = \text{fib}[k-1] + \text{fib}[k-2] \end{array} \right.$

~~fib~~  $\text{fib}[k] = f$

return  $\text{fib}[n]$

- exactly same computation
- topological sort of subproblem dependency DAG

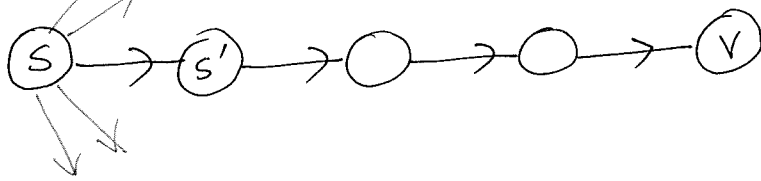


- can save space

5

Shortest paths  $\delta(s, v) \forall v$  SSSP

- Guess the first edge (outgoing edge)



- Guess the last edge (incoming edge)



$$\delta(s, v) = \min_{(u, v) \in E} \{ \delta(s, u) + w(u, v) \}$$

$\delta(s, s) = 0$  : base case

Guessing:

don't know the answer?

- guess

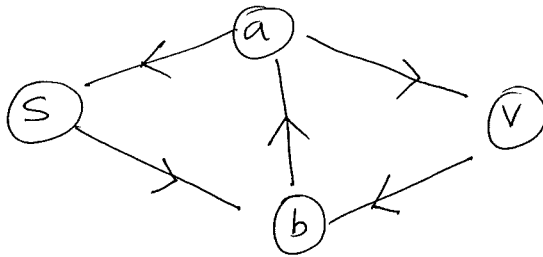
... try all guesses

& take the best one

Optimal substructure

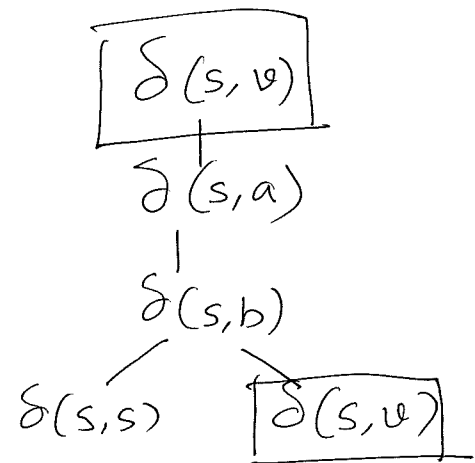
subpath of shortest paths are shortest paths

Is it a good algorithm?



"infinite algorithm"

on graphs with cycles



For DAGs :  $\Theta(V + E)$

time for subproblem  $\delta(s, v) = \text{indegree}(v) + 1$

$$\text{total time} = \sum_{v \in V} \text{indegree}(v) + 1 = \Theta(E + V)$$

Handshaking Lemma

"DFS to do a topological sort to do one round of Bellman Ford"  
 \* subproblem dependencies should be acyclic"

- What about graphs with cycles? no negative wt. cycles

⑥

$\delta_k(s, v)$  = weight of shortest path  $s \rightarrow v$  that uses at most  $k$  edges

$$\delta_k(s, v) = \min_{(u, v) \in E} \left( \delta_{k-1}(s, u) + w(u, v) \right) \quad \forall v \in V, 0 \leq k \leq |V|$$

# of subproblems =  $V^2$

goal:  $\delta_{|V|-1}(s, v)$

total running time =  $\Theta(VE)$

DP  $\approx$  guessing + recursion + memoization

5 steps in DP :

Step 1. Define subproblems and count # subproblems

Step 2. Guess (part of solution) and count # choices for guess

Step 3. Relate subproblem solutions and evaluate time/subproblem

Step 4. Recurse & memoize / build DP table bottom-up and make sure recurrences are acyclic

Step 5. Solve the original problem and evaluate total running time

5 steps of DP for Fibonacci and Shortest Path :

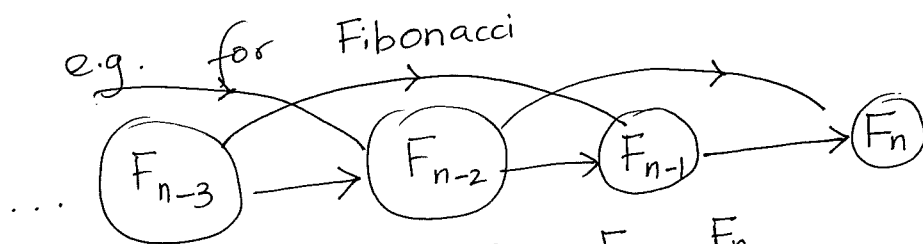
	<u>Fibonacci</u>	<u>Shortest Path</u>
Step 1	$F_k$ for $k=1, \dots, n$ $n$	$\delta_k(s, v)$ for $v \in V, 0 \leq k <  V $ $V^2$
Step 2	nothing 1	edge into $v$ (if any) $\text{indegree}(v) + 1$
Step 3	$F_k = F_{k-1} + F_{k-2}$ $\Theta(1)$	$\delta_k(s, v) = \min_{(u, v) \in E} \left\{ \delta_{k-1}(s, u) + w(u, v) \right\}$ $\Theta(\text{indegree}(v) + 1)$
Step 4	for $k=1, \dots, n$	for $k=0, 1, \dots,  V -1$ : for $v \in V$
Step 5	$F_n, \Theta(n)$	$\delta_{ V -1}(s, v) \quad \forall v \in V, \Theta(V^2)$

N.B DP is NOT the ONLY way to compute SSSP (7)  
Single Source Shortest Paths (SSSP) Algorithms and Complexities by Scenarios

<u>Scenarios</u>	<u>Algorithm</u>	<u>Complexity</u>
unweighted ( $w=1$ )	BFS	$O(V+E)$
non negative edge weights	Dijkstra	$O(V \log V + E)$ using Fibonacci Heap data structure
general	Bellman - Ford	$O(VE)$
acyclic (DAG)	topological sort + 1 round of Bellman - Ford	$O(V+E)$

### Traceback / Backtracking

- If you have the topological sort of subproblem dependency DAG, simply enumerate it to identify ~~first~~ the order in which the bigger subproblem is broken down into smaller ones (i.e. order of subprob)



- 1, 1, 2, ...,  $F_{n-3}$   $F_{n-2}$   $F_{n-1}$   $F_n$
- This is used for the optimal answer rather than the optimal value. e.g. in case of SSSP, we could be interested in ~~the~~ a shortest path itself rather than the sum of edge weights of shortest path.
  - Can be implemented in conjunction with memoization.

Longest Palindromic Subsequence Problem

Credits: Srinivas Devadas

Note: sequence: the original enumerated collection of objects (repetitions are allowed)

- subsequence: ~~ordered~~; it can be non-contiguous.

- substring: ~~ordered~~ must be contiguous.

Examples of palindrome: a, bb, radar

Problem Statement: Given a string  $X[1..n]$   $n \geq 1$ .  
find out longest palindrome that is a subsequence of  $X$  having length  $\geq 1$ .

e.g. turboventilator  
rotor (5) rotator (7)

Solution Define  $LPS(i, j)$  as the length of the longest palindromic subsequence of  $X[i..j]$  ;  $i \leq j$

$LPS(i, j)$ :

if  $i = j$  : return 1

if  $X[i] = X[j]$  :

if  $i+1 = j$  : return 2

else : return  $2 + LPS(i+1, j-1)$

else : return  $\max(LPS(i+1, j), LPS(i, j-1))$

(\*) look at  $LPS[i, j]$  and memoize

Without memoization;  $T(n) = \begin{cases} 1 & n=1 \\ 2T(n-1) & n>1 \end{cases}$   
(exponential)  
 $= 2^{n-1}$

After memoization :

#subproblems. \*  $\frac{\text{time}}{\text{subproblem}} = n^2 \cdot \Theta(1) = \Theta(n^2)$