CSE 417: Algorithms and Computational Complexity

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Dynamic Programming, I
Fibonacci & Stamps

Dynamic Programming

Outline:

- General Principles
- Easy Examples – Fibonacci, Licking Stamps
- Meatier examples
  - RNA Structure prediction
  - Weighted interval scheduling
  - Maybe others

Some Algorithm Design Techniques, I

- General overall idea
  - Reduce solving a problem to a smaller problem or problems of the same type
- Greedy algorithms
  - Used when one needs to build something a piece at a time
  - Repeatedly make the *greedy* choice - the one that looks the best right away
    - e.g. closest pair in TSP search
  - Usually fast if they work (but often don't)

Some Algorithm Design Techniques, II

Divide & Conquer

- Reduce problem to one or more sub-problems of the same type
- Typically, each sub-problem is at most a constant fraction of the size of the original problem
  - e.g. Mergesort, Binary Search, Strassen's Algorithm, Quicksort (kind of)

Some Algorithm Design Techniques, III

Dynamic Programming

- Give a solution of a problem using smaller sub-problems, e.g. a recursive solution
- Useful when the same sub-problems show up again and again in the solution

“Dynamic Programming”

Program — A plan or procedure for dealing with some matter

– Webster’s New World Dictionary

Dynamic Programming History

Bellman. Pioneered the systematic study of dynamic programming in the 1950s.

Etymology.

- Dynamic programming = planning over time.
- Secretary of Defense was hostile to mathematical research.
- Bellman sought an impressive name to avoid confrontation.
  - "it's impossible to use dynamic in a pejorative sense"
  - "something not even a Congressman could object to"

Reference: Bellman, R. E. *Eye of the Hurricane, An Autobiography.*

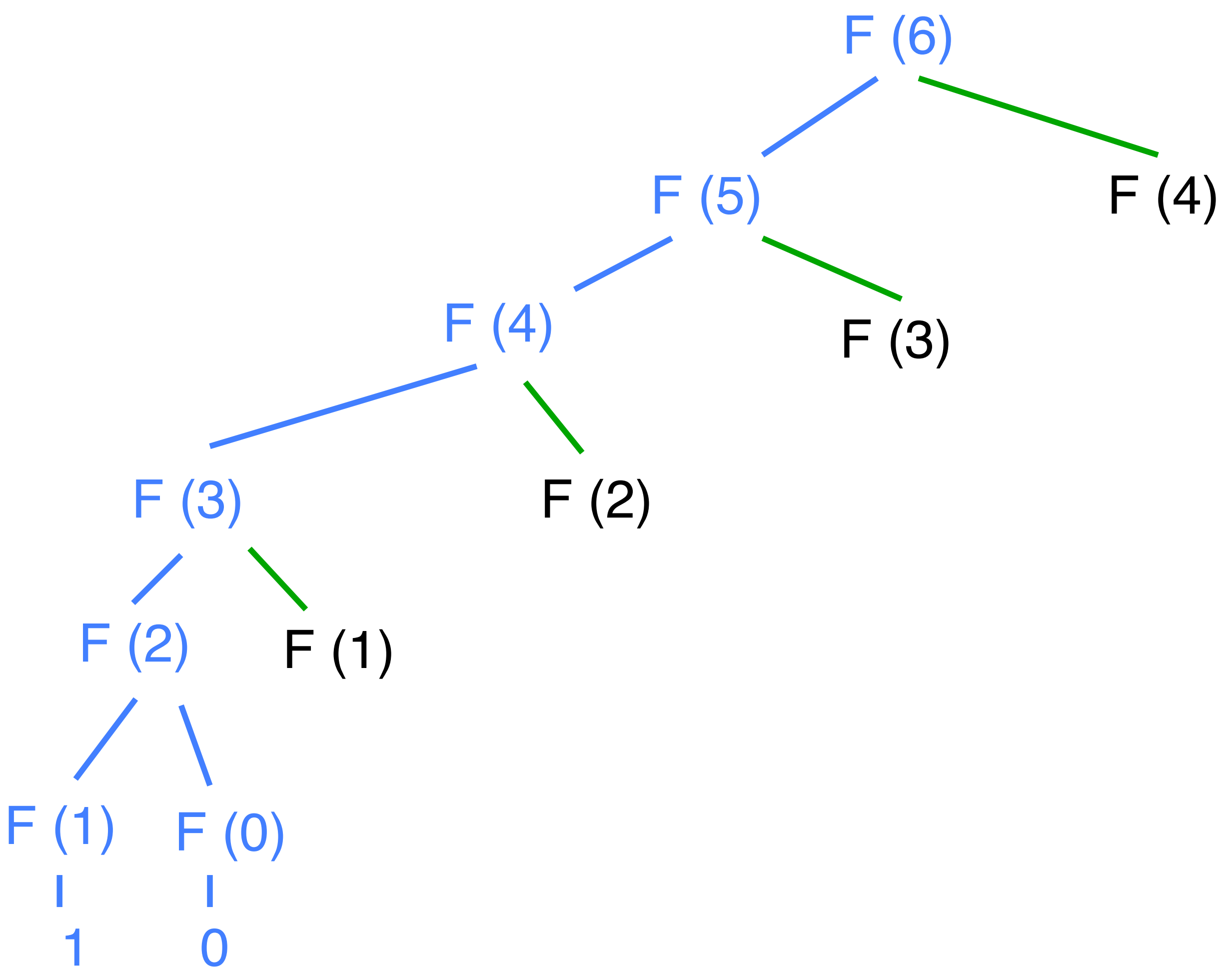
A very simple case: Computing Fibonacci Numbers

Recall $F_n = F_{n-1} + F_{n-2}$ and $F_0 = 0$, $F_1 = 1$

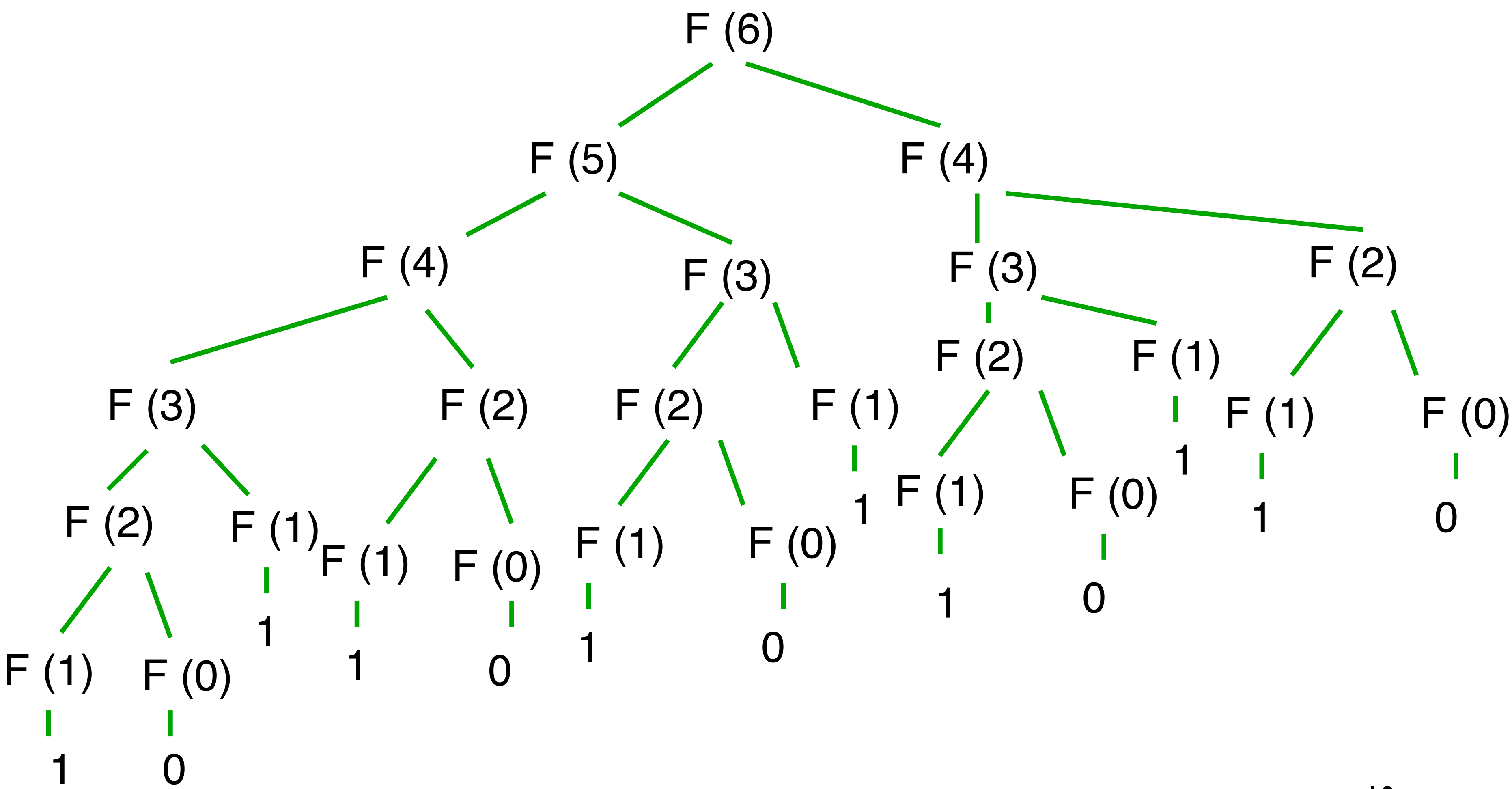
Recursive algorithm:

```
Fibo(n)
    if n=0 then return(0)
    else if n=1 then return(1)
    else return(Fibo(n-1)+Fibo(n-2))
```

Call tree - start



Full call tree



Memo-ization (Caching)

Remember all values from previous recursive calls

Before recursive call, test to see if value has already been computed

Dynamic Programming

- *NOT* memoized; instead, convert memoized alg from a recursive one to an iterative one (top-down → bottom-up)

Fibonacci - Memoized Version

```
initialize: F[i] ← undefined for all i
F[0] ← 0
F[1] ← 1
FiboMemo(n):
    if(F[n] undefined) {
        F[n] ← FiboMemo(n-2)+FiboMemo(n-1)
    }
    return(F[n])
```

Fibonacci - Dynamic Programming Version

```
FiboDP(n):
    F[0] ← 0
    F[1] ← 1
    for i=2 to n do
        F[i]  ← F[i-1]+F[i-2]
    endfor
    return(F[n])
```

For this problem, keeping only last 2 entries instead of full array suffices, but about the same speed

Dynamic Programming

Useful when

- Same recursive sub-problems occur repeatedly
- Parameters of these recursive calls anticipated
- The solution to whole problem can be solved without knowing the *internal* details of how the sub-problems are solved
    - "principle of optimality"

Making change

Given:

- Large supply of 1¢, 5¢, 10¢, 25¢, 50¢ coins
- An amount N

Problem: choose fewest coins totaling N

Cashier's (greedy) algorithm works:

- Give as many as possible of the next biggest denomination

Licking Stamps

Given:

- Large supply of 5¢, 4¢, and 1¢ stamps
- An amount N

Problem: choose fewest stamps totaling N

How to Lick 27¢

# of 5¢ stamps	# of 4 ¢ stamps	# of 1¢ stamps	total number
5	0	2	7
4	1	3	8
3	3	0	6

Morals: Greed doesn't pay; success of "cashier's alg" depends on coin denominations

A Simple Algorithm

At most N stamps needed, etc.

```
for a = 0, …, N {
   for b = 0, …, N {
      for c = 0, …, N {
         if (5a+4b+c == N && a+b+c is new min)
            {retain (a,b,c);}}}
output retained triple;
```

Time: $O(N^3)$

(Not too hard to see some optimizations, but we're after bigger fish…)

Better Idea

Theorem: If last stamp licked in an optimal solution has value v, then previous stamps form an optimal solution for N-v.

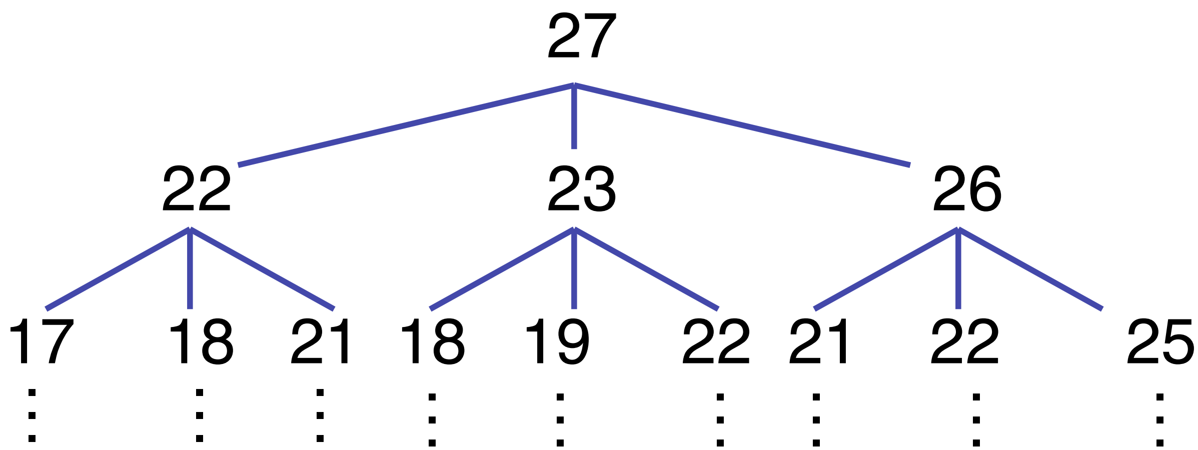
Proof: if not, we could improve the solution for N by using opt for N-v.

$$M(i) = \min \begin{Bmatrix} 0 & i=0 \\ 1+M(i-5) & i\geq 5 \\ 1+M(i-4) & i\geq 4 \\ 1+M(i-1) & i\geq 1 \end{Bmatrix}$$

where *M(i)* = min number of stamps totaling *i*¢

New Idea: Recursion

$$M(i) = \min \begin{Bmatrix} 0 & i=0 \\ 1+M(i-5) & i \geq 5 \\ 1+M(i-4) & i \geq 4 \\ 1+M(i-1) & i \geq 1 \end{Bmatrix}$$



Time: $> 3^{N/5}$

Another New Idea: Avoid Recomputation

Tabulate values of solved subproblems

- Top-down: “memoization”
- Bottom up:

for i = 0, …, N do $M[i] = \min \left\{ \begin{array}{ll} 0 & i=0 \\ 1+M[i-5] & i \geq 5 \\ 1+M[i-4] & i \geq 4 \\ 1+M[i-1] & i \geq 1 \end{array} \right\}$;

Time: O(N)

Finding How Many Stamps

i	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
M(i)	0	1	2	3	1	1	2	3	2						

1+Min(3,1,3) = 2

Finding Which Stamps: Trace-Back

i	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
M(i)	0	1	2	3	1	1	2	3	2						

4¢

1+Min(3,**1**,3) = **2**

Trace-Back

Way 1: tabulate all

add data structure storing back-pointers indicating which predecessor gave the min. (more space, maybe less time)

Way 2: re-compute just what's needed

```
TraceBack(i):
  if i == 0 then return;
  for d in {1, 4, 5} do
    if M[i] == 1 + M[i - d] then break;
  print d;
  TraceBack(i - d);
```

Complexity Note

O(N) is better than $O(N^3)$ or $O(3^{N/5})$

But still *exponential* in input size
(log N bits)

(E.g., miserable if N is 64 bits – $c \cdot 2^{64}$ steps & 2^{64} memory.)

Note: can do in O(1) for 5¢, 4¢, and 1¢ but not in general. See "NP-Completeness" later.

Elements of Dynamic Programming

What feature did we use?

What should we look for to use again?

“Optimal Substructure”

Optimal solution contains optimal subproblems

A non-example: min (number of stamps mod 2)

“Repeated Subproblems”

The same subproblems arise in various ways