Lecture 7: Dynamic Programming

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bit.ly/cs3000syllabus



Homework 2 is out, due Tuesday May 19 11:59PM Boston time on Canvas

We are working on grading homework 1, will share solutions once the grades are complete

It is totally fine to look ahead in the slides, but please give others a minute to try to answer questions I ask before writing what you saw later



Dynamic Programming Fibonacci Numbers Text Segmentation Revisited

Fibonacci Numbers

$$f_n \begin{cases} 0 & \text{ if } n = 0 \\ 1 & \text{ if } n = 1 \\ f_{n-1} + f_{n-2} & \text{ otherwise} \end{cases}$$

Fibonacci Numbers: Recursion

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What does the recurrence relation T(n) look like? T(0) = 1, T(1) = 1T(n) = T(n-1) + T(n-2) + 1

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First, if we squint and assume $n \rightarrow \infty$ we might see

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$$T(n) = T(n-1) + T(n-1) + 1$$

$$T(n) = 2T(n-1) + 1 \le 2 \cdot 2^{n}$$

$$\le O(2^{n+1})$$

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T(2) = T(1) + T(0) + 1 = 3

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Fib(n):
    If n = 0:
        return 0
    ElseIf n = 1:
        return 1
    Else:
        return Fib(n - 1) + Fib(n - 2)
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Exponential in *n* is *very* slow for such a simple function!

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Memoization

Fib(n): If n = 0: return 0 ElseIf n = 1: return 1 Else: return Fib(n - 1) + Fib(n - 2) Fib(n) is very slow because we are recomputing the same values over and over again!

Fib(n): If n = 0: return 0 ElseIf n = 1: return 1 Else: return Fib(n - 1) + Fib(n - 2)

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- What if instead we save each value we compute so that we can access it in constant time?

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- Keep a global table F[i] that stores results and use stored results where possible
- How is the table filled? And what implication does this have for the runtime?



Figure 3.2. The recursion tree for F_7 trimmed by memoization. Downward green arrows indicate writing into the memoization array; upward red arrows indicate reading from the memoization array.

How many additions?



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There has to be a better way!



Enter: Dynamic programming

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 The execution order and runtime of *MemFib(n)* implies a simpler way to compute Fibonacci numbers

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IterFib(n):
F[0] \leftarrow 0
F[1] \leftarrow 1
for i from 2..n
F[i] \leftarrow F[i-1] + F[i-2]
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- The execution order and runtime of *MemFib(n)* implies a simpler way to compute Fibonacci numbers
- What if we just like....filled *F* explicitly?

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- The execution order and runtime of *MemFib(n)* implies a simpler way to compute Fibonacci numbers
- What if we just like....filled *F* explicitly?
- Now the execution is clearly O(n)!
- Note: We could save memory here. How?

- Formalized by Richard Bellman at RAND in the '50s
 - Bellman apparently named it "dynamic programming" to obscure his research from his bosses.
 - Programming does not refer to computers, but scheduling: for example designing the "program" of a performance or event, or filling a TV schedule
- General pattern: Recursion without repetition
 - Store solutions of intermediate problems to be reused later!
 - Finding a correct recurrence that can be memoized is vital
 - If your recurrence is wrong or can't be memoized, you will go in circles!

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There are 3 main steps to developing dynamic programming solutions:

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 - Formalize the problem carefully
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 - What are the subproblems that need solving?
 - What data structure can I use to access them correctly and quickly?
 - Which subproblems depend on each other?
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- 3. Prove it!

 $T(n) = 2T(n-1) + c \le O(2^n)$

```
Splittable(A[1..n],i):
    If i > n:
        return True
Else:
        j \leftarrow i
        for j to n:
        If IsWord(i,j):
        If Splittable(A[1..n], j + 1):
        return True
```

return False

Problem: Given an array A[1..n]representing a sequence of n characters without spaces, determine whether the array can be subdivided into a sequence of *words*.

Assume we are given a function IsWord(i, j). This function assumes A is a global variable and returns True if the subarray A[i..j] is a word in the language of the sequence.

• This allows us to avoid passing subarrays as arguments to functions.

Where are we wasting computation?

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For all indices $1 \le i \le j \le n$, how many times can we call IsWord(i, j)?

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For a fixed A[1..n], how many ways can we call Splittable(A, i)?

O(n)

For all indices $1 \le i \le j \le n$, how many times can we call IsWord(i, j)?

 $O(n^2)$

We are spending exponential time computing polynomial amounts of stuff!

```
FastSplittable(A[1..n]):
SplitTable[n + 1] \leftarrow True
```

```
for i from n to 1:

SplitTable[i] \leftarrow False

for j from i to n:

If IsWord(i,j) AND SplitTable[j+1]:

SplitTable[i] \leftarrow True
```

return SplitTable[1]

n = 18



n = 18



n = 18



j + 1 = 19

n = 18



n = 18



n = 18



j + 1 = 14

n = 18



n = 18



Dynamic Programming Approach n = 18f t h b r k е 0 w n X S q u С 0 Ι j = 3i = 1FastSplittable(A[1..n]): $SplitTable[n + 1] \leftarrow True$ *IsWord*(1,3) is *True*! for i from n to 1: $SplitTable[i] \leftarrow False$ for j from i to n: If IsWord(i, j) AND SplitTable[j + 1]: *SplitTable* $SplitTable[i] \leftarrow True$ k t h е b w n Х q u С r 0 0 S return *SplitTable*[1] F F F F F F F F F F F F j + 1 = 4i = 1



If T propagates all the way back to i = 1, we have a segmentation!

FastSplittable Analysis

t	h	e	b	r	ο	w	n	f	ο	x	i	S	q	u	i	с	k	
Т	F	F	Т	F	Т	F	F	Т	Т	F	Т	F	Т	F	F	F	F	Т

FastSplittable(A[1..n]):SplitTable[n + 1] \leftarrow True

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for i from n to 1:
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return SplitTable[1]

If T propagates all the way back to i = 1, we have a segmentation!

Previously we had the recurrence:

 $T(n) = 2T(n-1) + c \le O(2^n)$

I argue we can just read off the running time of *FastSplittable* from the pseudocode

Wrap up

Work on homework 2! Due Tuesday night at midnight.

Next time:

- Subset Sum revisited
- Edit Distance
- Knapsack problem

No new reading assignment (Chapter 3 Erickson)