

Dynamic  
Programming

Gilles  
Englebert

What is  
Dynamic  
Programming?

The Fibonacci  
Sequence

The Knapsack  
Problem

Longest  
Decreasing  
Subsequence

Problems

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# Dynamic Programming

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# Overview

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# What is Dynamic Programming?

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**Dynamic Programming** or **memoization** is the a way to speed up recursive computations (i.e. solving a problem in terms of one or more smaller/simpler instances of the same problem) by saving intermediate results to memory instead of doing the same computation multiple times. It is a **tradeoff** between memory and computation, and is most useful when sub-problems **overlap**.

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The **Fibonacci sequence**  $F_n (n \geq 0)$  is defined as  $F_0 = 0$ ,  $F_1 = 1$  and  $F_n = F_{n-1} + F_{n-2}$  for  $n \geq 2$ . Or in C++:

```
int fib (int n) {  
    if (n <= 1) return n;  
    return fib (n-1)+fib (n-2);  
}
```

What is the runtime of this recursive approach? How many computations do we really perform to determine  $F_n$ ?

The runtime is  $O(n!)$  (where ! is the factorial  $n! = n(n-1)(n-2)\dots 2 \cdot 1$ ).

We only compute  $n + 1$  different values ( $F_0$  up to  $F_n$ )

# Solution

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We can save to memory the intermediate computations. This is called the **top-down** approach.

```
int f[1000] = {0};
int fib(int n) {
    if (n <= 1) return n;
    if (f[n] != 0) return f[n];

    f[n] = fib(n-1)+fib(n-2);
    return f[n];
}
```

The new runtime is  $O(n)$ , but we also have to allocate  $O(n)$  memory, which we did not have to before (kind of).

# Better Solution

We can do the computation using only  $O(1)$  additional memory, using a **bottom-up** approach.

```
int f[2];
f[0] = 0;
f[1] = 1;
int fib(int n) {
    for (int i = 2; i <= n; i++)
        f[i%2] += f[(i+1)%2];

    return f[n%2];
}
```

This has the downside of being considerably harder to implement, but it can be worth it sometimes (e.g. when the DP array is only sparsely populated).

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# Even better Solution

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There is a very clever way do compute  $F_n$  in  $O(\log n)$ , using fast matrix exponentiation. I encourage you to look it up yourselves!

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You are given  $n$  objects that have weight  $w_i$  units and value  $p_i$  respectively. You also have a bag (= knapsack) which can hold objects with a total weight of at most  $C$  units. What is the most expensive set of objects (i.e. highest total value) you can put in your bag?

## Example

$n = 3$  and  $C = 5$  with  $w = \{3, 3, 5\}$ ,  $p = \{5, 5, 6\}$ .

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We iterate through the objects one after another and go through any possible combinations of objects using recursive brute force.

```
int w[n]; //Weights
int p[n]; //Value/Price
int knap(int c, int i) {
    if (c < 0) return NEGATIVE_INFINITY;
    if (i > n) return 0;

    return max(knap(c, i+1),
               knap(c-w[i], i+1)+p[i]);
}
```

Runtime  $O(2^n)$ , memory  $O(n)$ .

# Better solution

We realise that once we get to the  $i$  – *th* object, all we need is  $knap(\tilde{c}, it)$  for every  $0 \leq \tilde{c} \leq C$ .

```
int w[n]; //Weights
int p[n]; //Value/Price
int dp[C][n] = {-1};
int knap(int c, int i) {
    if (c < 0) return NEGATIVE_INFINITY;
    if (i > n) return 0;

    if (dp[c][i] == -1)
        dp[c][i] = max(knap(c, i+1),
            knap(c-w[i], i+1) +p[i]);
    return dp[c][i]; }
```

Runtime  $O(nC)$ , memory  $O(nC)$ . We traded more memory for a faster execution.

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## Problem

*Given an array  $a[1 \dots n]$  of  $n$  integers, compute the length of the longest strictly decreasing subsequence  $\text{LDS}(a)$  of  $a$ .*

## Example

Let  $a[1 \dots 6] = \{5, 3, 4, 3, 3, 1\}$ . Then  $\text{LDS}(a) = 4$ .

# Solution in $O(n^2)$

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## Solution

*Let  $dp[i]$  denote the maximal length of a decreasing subsequence ending at index  $i$ . Then*

$$dp[i + 1] = \max\{1\} \cup \{dp[j] + 1 : a[j] > a[i], 1 \leq j \leq i \leq n\}$$

*Then  $LDS(a) = \max_{1 \leq i \leq n} dp[i]$ .*

# Editing Distance

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## Problem

Let  $s, t$  be two strings of length  $m$  and  $n$  respectively. The **editing distance**  $\text{Edit}(s, t)$  between  $s$  and  $t$  is the minimum number of replacements, deletions and additions of single characters to be performed on  $s$  to obtain  $t$ . Compute  $\text{Edit}(s, t)$  efficiently.

## Example

Let  $s = \text{"kitten"}$  and  $t = \text{"sitting"}$ , then  $\text{Edit}(s, t) = 3$ .

The editing distance is important in genetics, where it is used as a measure of similarity between two segments of DNA.

# Traveling Salesman

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## Problem

*Given  $n$  cities with pairwise distances  $d[1 \dots n][1 \dots n]$ , what is the minimal cost of completing a a loop which visits every city exactly once?*

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Here are some further problems (clickable links!):

[LIO 2023 - Traffic Control](#)

[LIO 2020 - Packaging](#)

[LIO 2019 - Peche](#)

[LIO 2016 - Champignons](#)

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And some references (also clickable!)

Competitive Programming book

USACO

Also, if you have any questions, don't hesitate to write me at  
gilles@englebert.lu.