Introduction to Dynamic Programming

Florian Gatignon November 4, 2018

Swiss Olympiad in Informatics

- 1. Introduction
 - 1.1 What is dynamic programming?
 - 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

1. Introduction

- 1.1 What is dynamic programming?
- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

1. Introduction

1.1 What is dynamic programming?

- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

• not an algorithm

- **not** an algorithm
- a technique

- **not** an algorithm
- a technique for solving problems (in particular optimization problems)

- not an algorithm
- a technique for solving problems (in particular optimization problems) more efficiently.

• Doing the same thing twice is bad.

- Doing the same thing twice is bad.
- When you use the same code more than once, you use a function.

- Doing the same thing twice is bad.
- When you use the same code more than once, you use a function.
- Your program should also be lazy and avoid to compute what it has already computed.

DP is a technique that you may use when you can divide a problem into subproblems and build the full solution using the partial solutions, but the subproblems overlap and you end up solving the same subproblems over and over again. DP is a technique that you may use when you can divide a problem into subproblems and build the full solution using the partial solutions, but the subproblems overlap and you end up solving the same subproblems over and over again.

A dynamic program avoids this problem by **remembering** what it has already done and not computing it again.

1. Introduction

1.1 What is dynamic programming?

1.2 A simple example: Fibonacci's sequence

- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

Fibonacci's sequence can be defined as follows:

$$\begin{cases} f_0 = 0 \\ f_1 = 1 \\ \forall n \in \mathbb{N} \setminus \{0, 1\}, f_n = f_{n-1} + f_{n-2} \end{cases}$$

Fibonacci's sequence can be defined as follows:

$$\begin{cases} f_0 = 0 \\ f_1 = 1 \\ \forall n \in \mathbb{N} \setminus \{0, 1\}, f_n = f_{n-1} + f_{n-2} \end{cases}$$

Here are a few first values of the sequence:

 $0, 1, 1, 2, 3, 5, 8, 13, 21, 34, \ldots$

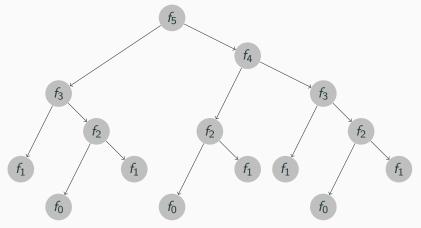
An intuitive way of computing values of the sequence would be:

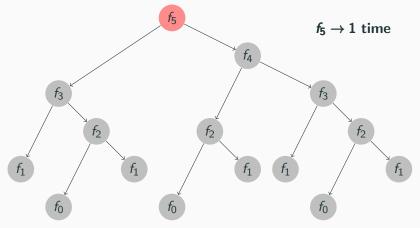
```
int fib(int n) {
    if(n==0) return 0;
    if(n==1) return 1;
    return fib(n-1) + fib(n-2);
}
```

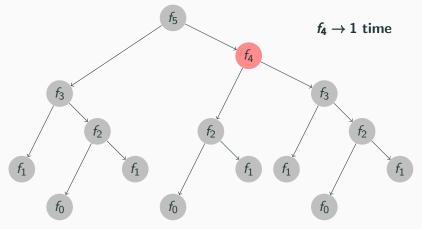
If you try to run this code to compute f_{100} , you'd have to be **very** patient to get an answer.

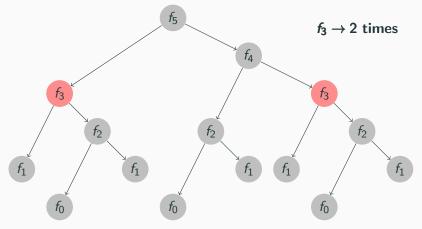
If you try to run this code to compute f_{100} , you'd have to be **very** patient to get an answer.

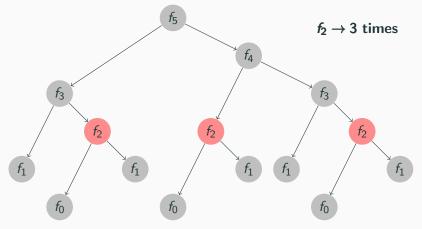
Why?

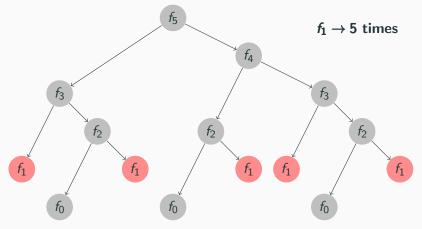


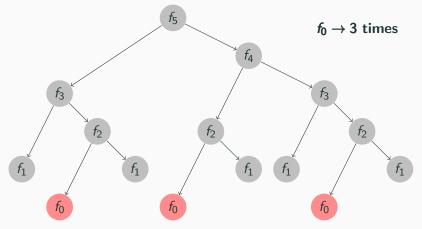












This example shows us that the number of operations increases at the same speed as the results (the number of times we compute each value are all increasing values of Fibonacci's sequence)! This example shows us that the number of operations increases at the same speed as the results (the number of times we compute each value are all increasing values of Fibonacci's sequence)! The Fibonacci sequence grows exponentially, so we have an exponential running time... We can do (much) better.

We can do (much) better. We don't need to compute anything twice:

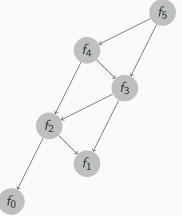
We can do (much) better. We don't need to compute anything twice:

Just remember the previous values!

We can do (much) better. We don't need to compute anything twice:

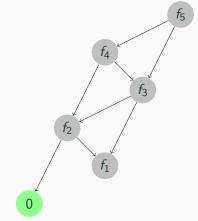
Just remember the previous values! We can first compute lower values and then combine them to get the next one.

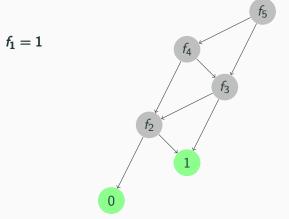
We can use already computed values to build the higher ones in order:

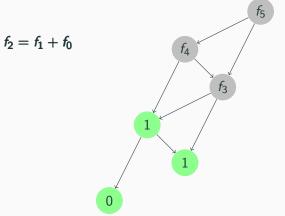


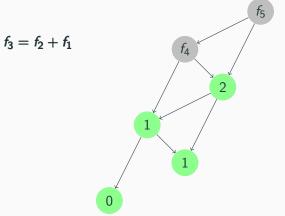
We can use already computed values to build the higher ones in order:

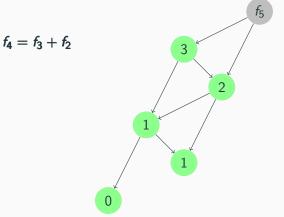
 $f_0 = 0$

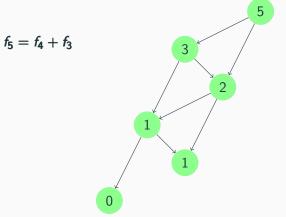












We compute all values (once) from f_0 up to f_n :

```
int fib(int n) {
    vector<int> v;
    v.push_back(0);
    v.push_back(1);
    for(int i = 2; i <= n; i++) {
        v.push_back(v[v.size()-1] + v[v.size()-2]);
    }
    return v[n];
}</pre>
```

We compute all values (once) from f_0 up to f_n :

```
int fib(int n) {
    vector<int> v:
    v.push_back(0);
    v.push_back(1);
    for(int i = 2; i <= n; i++) {</pre>
        v.push_back(v[v.size()-1] + v[v.size()-2]);
    }
    return v[n];
}
```

Our running time is now down to...

We compute all values (once) from f_0 up to f_n :

```
int fib(int n) {
    vector<int> v:
    v.push_back(0);
    v.push_back(1);
    for(int i = 2; i <= n; i++) {</pre>
        v.push_back(v[v.size()-1] + v[v.size()-2]);
    }
    return v[n];
}
```

Our running time is now down to $\mathcal{O}(n)$.

Bonus solution: you don't need $\mathcal{O}(n)$ space.

```
int fib(int n) {
    int a = 0, b = 1;
    for(int i = 0; i < n; i++) {
        swap(a,b);
        b += a;
    }
    return a;
}</pre>
```

Bonus solution: you don't need $\mathcal{O}(n)$ space.

```
int fib(int n) {
    int a = 0, b = 1;
    for(int i = 0; i < n; i++) {
        swap(a,b);
        b += a;
    }
    return a;
}</pre>
```

There's an even better solution in $\mathcal{O}(\log(n))$, but it is not in our scope for today.

The recipe for creating a good DP solution

1. Introduction

- 1.1 What is dynamic programming?
- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

This was a simple example, but the same schemata apply to much more complicated problems. We shall now generalize what we've learned from Fibonacci's sequence and apply it to other problems.

1. Introduction

- 1.1 What is dynamic programming?
- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

Think first, code second!

1. Define subproblems.

- 1. Define subproblems.
- 2. Find a general recurrence formula to solve a subproblem using the solution to other subproblems.

- 1. Define subproblems.
- 2. Find a general recurrence formula to solve a subproblem using the solution to other subproblems.
- 3. Find base case(s).

- 1. Define subproblems.
- 2. Find a general recurrence formula to solve a subproblem using the solution to other subproblems.
- 3. Find base case(s).
- 4. Which is the relevant subproblem?

1. Introduction

- 1.1 What is dynamic programming?
- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

1. Suproblems:

1. Suproblems: f_i .

- 1. Suproblems: f_i.
- 2. General formula:

- 1. Suproblems: f_i .
- 2. General formula: $f_i = f_{i-1} + f_{i-2}$.

- 1. Suproblems: f_i .
- 2. General formula: $f_i = f_{i-1} + f_{i-2}$.
- 3. Base cases:

- 1. Suproblems: f_i.
- 2. General formula: $f_i = f_{i-1} + f_{i-2}$.
- 3. Base cases: $f_0 = 0, f_1 = 1$.

- 1. Suproblems: f_i .
- 2. General formula: $f_i = f_{i-1} + f_{i-2}$.
- 3. Base cases: $f_0 = 0, f_1 = 1$.
- 4. Relevant suproblem:

- 1. Suproblems: f_i.
- 2. General formula: $f_i = f_{i-1} + f_{i-2}$.
- 3. Base cases: $f_0 = 0, f_1 = 1$.
- 4. Relevant suproblem: f_n .

1. Introduction

- 1.1 What is dynamic programming?
- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

— Okay, I've followed your four steps. How do I use this to code a solution now?

Most subproblems can be solved only using other subproblems.

Most subproblems can be solved only using other subproblems. In what order can we compute subproblems?

Most subproblems can be solved only using other subproblems. In what order can we compute subproblems?

1. Start with the base cases. We know the answer for those.

Most subproblems can be solved only using other subproblems. In what order can we compute subproblems?

- 1. Start with the base cases. We know the answer for those.
- 2. Compute other subproblems which only need base cases.

Most subproblems can be solved only using other subproblems. In what order can we compute subproblems?

- 1. Start with the base cases. We know the answer for those.
- 2. Compute other subproblems which only need base cases.
- 3. Continue computing further subproblems which are now solvable.

Most subproblems can be solved only using other subproblems. In what order can we compute subproblems?

- 1. Start with the base cases. We know the answer for those.
- 2. Compute other subproblems which only need base cases.
- 3. Continue computing further subproblems which are now solvable.
- 4. When the relevant subproblem is found, return the result!

Most subproblems can be solved only using other subproblems. In what order can we compute subproblems?

- 1. Start with the base cases. We know the answer for those.
- 2. Compute other subproblems which only need base cases.
- 3. Continue computing further subproblems which are now solvable.
- 4. When the relevant subproblem is found, return the result!

This is the hardest part of most difficult dynamic programming problems. Sometimes, a viable ordering is obvious, sometimes it is not; the best way to get used to it is to solve a lot of this kind of problems.

1. Introduction

- 1.1 What is dynamic programming?
- 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate
- 3. Conclusion

Renovate: Task statement

• You're given a *n* × *m* rectangle "wall" made of zeroes and ones as input.

- You're given a *n* × *m* rectangle "wall" made of zeroes and ones as input.
- Your task is to renovate the wall.

- You're given a *n* × *m* rectangle "wall" made of zeroes and ones as input.
- Your task is to renovate the wall.
- When there's a one at some coordinate, the wall is in good shape at this position, so you leave it as it is.

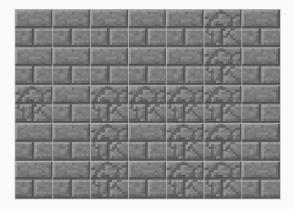
- You're given a *n* × *m* rectangle "wall" made of zeroes and ones as input.
- Your task is to renovate the wall.
- When there's a one at some coordinate, the wall is in good shape at this position, so you leave it as it is.
- When there's a zero, this section of the wall is holey, and you have two choices: turn it into a window, or rebuild a solid wall at this place.

- You're given a *n* × *m* rectangle "wall" made of zeroes and ones as input.
- Your task is to renovate the wall.
- When there's a one at some coordinate, the wall is in good shape at this position, so you leave it as it is.
- When there's a zero, this section of the wall is holey, and you have two choices: turn it into a window, or rebuild a solid wall at this place.
- Every window needs a full column of solid walls on both its left and its right in order not to affect the stability of the wall.

- You're given a *n* × *m* rectangle "wall" made of zeroes and ones as input.
- Your task is to renovate the wall.
- When there's a one at some coordinate, the wall is in good shape at this position, so you leave it as it is.
- When there's a zero, this section of the wall is holey, and you have two choices: turn it into a window, or rebuild a solid wall at this place.
- Every window needs a full column of solid walls on both its left and its right in order not to affect the stability of the wall.
- Maximize the number of windows!

1	1	1	1	1	0	1	
1	1	1	1	1	0	1	
0	1	0	0	0	0	1	
1	1	0	1	0	0	1	
1	1	0	1	0	0	1	

This is our input. Zeroes are broken parts of the wall and ones are solid parts of the wall.

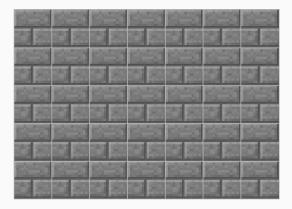


Let's use images as a clearer representation of this example.

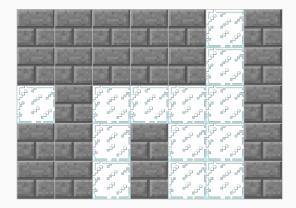




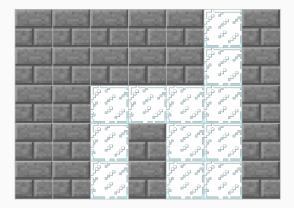
For every hole, we must decide if we fill it with a wall or with a window.



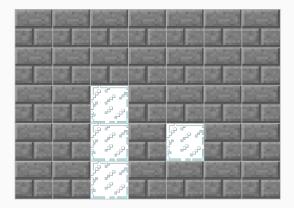
It is always possible to have a complete wall without any windows. Of course, this is very rarely optimal.



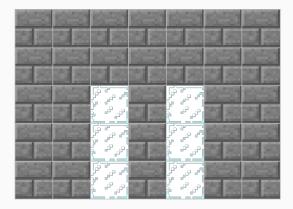
Building windows in every holey part of the wall is not always possible. For example, the wall here is not stable at all.



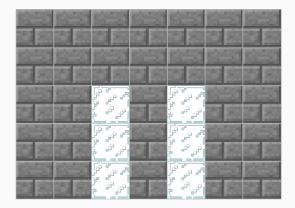
You can't have a window in the leftmost column, because there's no wall on its left. But removing it is still not enough: the wall is still unstable.



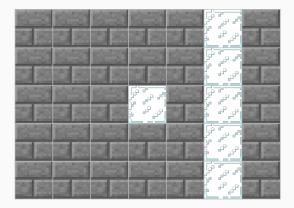
You always have to build two full columns around the windows that you build.



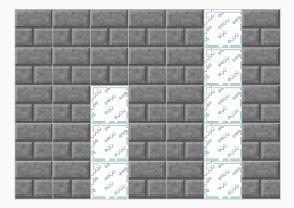
If you build a window in a column, it's always optimal to build all possible windoww in that column. because you don't need to sacrifice any further possible windows in order to build them.



This is not optimal: 6 windows.



This is not optimal: 6 windows.



This is optimal: 8 windows.

• We reduce the problem to a one-dimensional problem: compute the number of possible windows in every column (we always either build none or all of them).

- We reduce the problem to a one-dimensional problem: compute the number of possible windows in every column (we always either build none or all of them).
- We set the number of possible windows in the leftmost and rightmost columns to 0.

- We reduce the problem to a one-dimensional problem: compute the number of possible windows in every column (we always either build none or all of them).
- We set the number of possible windows in the leftmost and rightmost columns to 0.

We start by computing an array w[m]. For every $0 \le i < m$, let w[i] be the number of possible windows in the *i*-th column.

Renovate: Precomputation

```
int main(){
    int n, m; // n = height, m = width
    cin >> n >> m:
    // w[i] = number of holes in the i-th column
    vector<int> w(m, 0);
    for(int i = 0; i < n; i++) {</pre>
        for(int j = 0; j < m; j++) {</pre>
            int c;
            cin >> c;
            w[j] += c == 0; // this section is holey
        }
    }
    w[0] = 0; w[m-1] = 0; // no window on the edges
    ... // actual computation
```

How do we modelize this problem using the four steps ?

Our general subproblem will be

Our general subproblem will be s_i , the maximal number of windows using the first i + 1 columns for any $0 \le i < m$.

When trying to compute s_i , the solution for i, we have two possibilities:

When trying to compute s_i , the solution for i, we have two possibilities:

1. We don't build the windows in the *i*-th column.

When trying to compute s_i , the solution for i, we have two possibilities:

- 1. We don't build the windows in the *i*-th column.
- 2. We do build the windows in the *i*-th column. In that case, we can't have any windows in the (i 1)-th column.

1. If we don't build the windows in the *i*-th column, $s_i =$

1. If we don't build the windows in the *i*-th column, $s_i = s_{i-1}$.

- 1. If we don't build the windows in the *i*-th column, $s_i = s_{i-1}$.
- 2. If we do build the windows in the *i*-th column, we can't use the (i 1)-th column's windows, but we can add the windows from the *i*-th column. Thus, $s_i =$

How does this translate into a formula?

- 1. If we don't build the windows in the *i*-th column, $s_i = s_{i-1}$.
- 2. If we do build the windows in the *i*-th column, we can't use the (i 1)-th column's windows, but we can add the windows from the *i*-th column. Thus, $s_i = s_{i-2} + w[i]$.

How does this translate into a formula?

- 1. If we don't build the windows in the *i*-th column, $s_i = s_{i-1}$.
- 2. If we do build the windows in the *i*-th column, we can't use the (i 1)-th column's windows, but we can add the windows from the *i*-th column. Thus, $s_i = s_{i-2} + w[i]$.

Since s_i should be optimal, we take the highest of these values.

How does this translate into a formula?

- 1. If we don't build the windows in the *i*-th column, $s_i = s_{i-1}$.
- 2. If we do build the windows in the *i*-th column, we can't use the (i 1)-th column's windows, but we can add the windows from the *i*-th column. Thus, $s_i = s_{i-2} + w[i]$.

Since s_i should be optimal, we take the highest of these values.

$$s_i = \max(s_{i-1}, s_{i-2} + w[i])$$

We need two base cases, because our formula goes two steps back.

We need two base cases, because our formula goes two steps back.

s₀ = w[0] = 0 (you can never build windows in the first column).

We need two base cases, because our formula goes two steps back.

- s₀ = w[0] = 0 (you can never build windows in the first column).
- s₁ = w[1] (since there are never any windows in the first column, it is always optimal to build the second column's windows if you don't take into account the next columns).

The relevant subproblem is the one including all columns, so the subproblem we want to compute is $s_{...}$

The relevant subproblem is the one including all columns, so the subproblem we want to compute is s_{m-1} .

The relevant subproblem is the one including all columns, so the subproblem we want to compute is $s_{m-1}(=s_{m-2})$, if m > 1.

Like for Fibonacci's sequence, we could use this recurrence formula and these base cases and get a slow, but correct, solution.

```
int s(int i, vector<int> &w) {
    if(i < 2) return w[i]; // base cases
    return max(s(i-1, w), s(i-2, w) + w[i]);
}</pre>
```

We do not, however, want to compute subproblems twice. We just compute them in the order in which they're needed and store them.

We do not, however, want to compute subproblems twice. We just compute them in the order in which they're needed and store them. The order in which they're needed, like for Fibonacci's sequence, is pretty obvious. Every subproblem relies on earlier subproblems only, so we solve them in increasing order.

i	w[i]	Vi
0	0	Optimal number of windows for the first 1 column
1	0	Optimal number of windows for the first 2 columns
2	3	Optimal number of windows for the first 3 columns
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	V _i
0	0	w[0] (base case)
1	0	Optimal number of windows for the first 2 columns
2	3	Optimal number of windows for the first 3 columns
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	Optimal number of windows for the first 2 columns
2	3	Optimal number of windows for the first 3 columns
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vį
0	0	0
1	0	w[1] (base case)
2	3	Optimal number of windows for the first 3 columns
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	Optimal number of windows for the first 3 columns
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	$\max(v_1, v_0 + w[2])$
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	Optimal number of windows for the first 4 columns
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	$\max(v_2, v_1 + w[3])$
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	3
4	3	Optimal number of windows for the first 5 columns
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	3
4	3	$\max(v_3, v_2 + w[4])$
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	3
4	3	6
5	5	Optimal number of windows for the first 6 columns
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	3
4	3	6
5	5	$\max(v_4, v_3 + w[4])$
6	0	Optimal number of windows for all columns

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	3
4	3	6
5	5	8
6	0	Optimal number of windows for all columns

i	w[i]	V _i
0	0	0
1	0	0
2	3	3
3	1	3
4	3	6
5	5	8
6	0	$\max(v_5, v_4 + w[4])$

Renovate: Computation

Step by step: sample case

i	w[i]	Vi
0	0	0
1	0	0
2	3	3
3	1	3
4	3	6
5	5	8
6	0	8

i	Vi
0	Optimal number of windows for the first 1 column
1	Optimal number of windows for the first 2 columns
2	Optimal number of windows for the first 3 columns
3	Optimal number of windows for the first 4 columns
4	Optimal number of windows for the first 5 columns
•••	
m-1	Optimal number of windows for all columns

i	Vi
0	w[0] (base case)
1	Optimal number of windows for the first 2 columns
2	Optimal number of windows for the first 3 columns
3	Optimal number of windows for the first 4 columns
4	Optimal number of windows for the first 5 columns
•••	
m-1	Optimal number of windows for all columns

i	Vi
0	w[0] (base case)
1	w[1] (base case)
2	Optimal number of windows for the first 3 columns
3	Optimal number of windows for the first 4 columns
4	Optimal number of windows for the first 5 columns
m-1	Optimal number of windows for all columns

i	Vi
0	w[0] (base case)
1	w[1] (base case)
2	$max(v_1, v_0 + w[2])$
3	Optimal number of windows for the first 4 columns
4	Optimal number of windows for the first 5 columns
m-1	Optimal number of windows for all columns

i	Vi
0	w[0] (base case)
1	w[1] (base case)
2	$max(v_1, v_0 + w[2])$
3	$max(v_2, v_1 + w[3])$
4	Optimal number of windows for the first 5 columns
m-1	Optimal number of windows for all columns

i	Vi
0	w[0] (base case)
1	w[1] (base case)
2	$max(v_1, v_0 + w[2])$
3	$max(v_2, v_1 + w[3])$
4	$max(v_3, v_2 + w[4])$
m-1	Optimal number of windows for all columns

i	Vi
0	w[0] (base case)
1	w[1] (base case)
2	$max(v_1, v_0 + w[2])$
3	$max(v_2, v_1 + w[3])$
4	$max(v_3, v_2 + w[4])$
•••	
m-1	$max(v_m - 2, v_m - 3 + w[m - 1])$ (relevant subproblem)

}

... // precomputation
vector<int> s(m);
s[0] = 0; s[1] = w[1]; // base cases
for(int i = 2; i < m; i++)
 s[i] = max(s[i-1], s[i-2] + w[i]);
cout << s[m-1] << '\n'; // relevant subproblem</pre>

How fast does this solution run?

How fast does this solution run? $\mathcal{O}(nm)$ (because of the input; after our precomputations, we solve the problem in $\mathcal{O}(m)$).

Conclusion

- 1. Introduction
 - 1.1 What is dynamic programming?
 - 1.2 A simple example: Fibonacci's sequence
- 2. The recipe for creating a good DP solution
 - 2.1 DP's four steps
 - 2.2 DP's four steps and Fibonacci's sequence
 - 2.3 How to implement a DP solution
 - 2.4 Another example: Renovate

3. Conclusion

• When you can divide a problem into subproblems.

- When you can divide a problem into subproblems.
- When the subproblems overlap.

- When you can divide a problem into subproblems.
- When the subproblems overlap.
- For example, it enables you to compute some recursive functions faster, for example Fibonacci's sequence.

- When you can divide a problem into subproblems.
- When the subproblems overlap.
- For example, it enables you to compute some recursive functions faster, for example Fibonacci's sequence.
- A lot of optimization problems require a dynamic programming solution.

- When you can divide a problem into subproblems.
- When the subproblems overlap.
- For example, it enables you to compute some recursive functions faster, for example Fibonacci's sequence.
- A lot of optimization problems require a dynamic programming solution.
- DP is often applied in problems with more than one dimension. In that case, finding the order of computation may be more difficult than usual.

It is also possible to keep the recursive function and store already stored values, for example in a map.

```
vector<int> m(MAX_N);
int fib(int n) {
    if(n<2) return n;
    if(m[n]) return m[n];
    return m[n] = fib(n-1) + fib(n-2);
}
```

It is also possible to keep the recursive function and store already stored values, for example in a map.

```
vector<int> m(MAX_N);
int fib(int n) {
    if(n<2) return n;
    if(m[n]) return m[n];
    return m[n] = fib(n-1) + fib(n-2);
}
```

Just like in the case of Fibonacci's sequence and Renovate, it is not, however, necessary to store all previous values. Recursion can also cause further problems (stack limit exceeded). The approach we used, building up the solutions in order, is called "bottom-up", and it is good to get used to it.

How to be good at DP

• DP is hard

• DP is hard for most people.

- DP is hard for most people.
- The concept is simple, but...

- DP is hard for most people.
- The concept is simple, but applying it to a problem and implementing the solution is difficult.

- DP is hard for most people.
- The concept is simple, but applying it to a problem and implementing the solution is difficult.
- Always think before you code!

- DP is hard for most people.
- The concept is simple, but applying it to a problem and implementing the solution is difficult.
- Always think before you code!
- Most important of all: solve, solve, solve!

What's next: Solve DP tasks on the grader. Next lecture: Subset Sum.