

Dynamic Programming & Split and List

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Dynamic Programming – Outline

- Most of you **know** Dynamic Programming (DP) :)
- Many struggle to **apply** it :(
 - How to identify a DP problem
 - How to tackle it
 - How to implement it
- Today we **start from scratch**
- Focus on solving Algolab problems with DP

First Example: Fibonacci Numbers

Definition: $F_1 = 1$, $F_2 = 1$, and $F_n = F_{n-1} + F_{n-2}$ for $n > 2$

Task: compute F_n .

Solution: transform definition into recursive algorithm.

```
1      int f(int i) {  
2          if(i == 1 || i == 2) return 1;  
3          return f(i-1) + f(i-2);  
4      }
```

Time complexity: $\Theta(\phi^n)$

Source of inefficiency? **Overlapping Subproblems...**

Fibonacci Numbers – Memoization

Recall: $F_1 = 1$, $F_2 = 1$, and $F_n = F_{n-1} + F_{n-2}$ for $n > 2$

Idea: do not recompute, **recall from memory**

```
1      map<int, int> memo;
2
3      int f(int i) {
4          if(i == 1 || i == 2) return 1;
5          if(memo[i] == memo.end()) // not in memory
6              memo[i] = f(i-1) + f(i-2);
7          return memo[i];
8      }
```

Time complexity: $\Theta(n)$

Memoization (or top-down DP) is **simple and powerful** :)

This was easy. Why is it difficult in general?

Essence of DP:

- Compute a solution from solutions of subproblems.
- Solve subproblems only once, by **storing results**.

Storing results is **easy**, just apply memoization.

Deriving a **recursive algorithm** is the **difficult part**!

Usually we do not get a recursive definition of the problem... :(

Second Example: Drink as much as possible

Task: given a sequence of n bottles with volumes v_1, \dots, v_n . Drink **as much** as you can, without drinking from two **adjacent** bottles.

We want a **recursive definition** for $f(i) :=$ "max amount we can drink from first i bottles".

- Base cases: $f(0) = 0$ and $f(1) = v_1$.
- $f(i) = \max\{v_i + f(i-2), f(i-1)\}$

Now we can transform this definition into a **recursive algorithm**.

```
1  int f(int i) {  
2      if(i == 0 || i == 1)  
3          return volumes[i] // trick: set volumes[0] = 0 ;)  
4      return max(volumes[i] + f(i-2), f(i-1));  
5  }
```

Time complexity: $\Theta(\phi^n)$ (same as Fibonacci)

Drink as much as possible – Memoization

Take recursive algorithm

```
1  int f(int i) {
2      if(i == 0 || i == 1)
3          return volumes[i] // trick: set volumes[0] = 0 ;)
4      return max(volumes[i] + f(i-2), f(i-1));
5  }
```

and simply add memo:

```
1  map<int, int> memo;
2
3  int f(int i) {
4      if(i == 0 || i == 1) return volumes[i];
5      if(memo[i] == memo.end())
6          memo[i] = max(volumes[i] + f(i-2), f(i-1));
7      return memo[i];
8  }
```

Time complexity: $\Theta(n)$

Find **recursive formulation** for the problem.

Implement it as recursive algorithm, it will be **correct** but **slow**.

Are there **overlapping subproblems**?

Add memoization!

What is left?

We focus on examples to illustrate particular difficulties that often occur in problems.

- Iterative DP (table, bottom-up)
- Compare memoization and iterative DP
- Reconstruct solutions
- Example with “complicated and many” subproblems

Drink as much as possible – Iterative DP

Recall: $f(0) = 0$ and $f(1) = v_1$ and $f(i) = \max\{v_i + f(i-2), f(i-1)\}$

We can easily transform this into an [iterative algorithm](#):

```
1  int f(int n) {  
2      vector<int> dp(n+1); // dp table  
3      dp[0] = 0;  
4      dp[1] = volumes[1];  
5      for(int i = 2; i <= n; ++i)  
6          dp[i] = max(volumes[i] + dp[i-2], dp[i-1]);  
7      return dp[n];  
8  }
```

The DP table [follows naturally](#) from recursive definition.

Memoization vs Iterative DP

Usually both work, so use what feels more natural to you ;)

Memoization:

- Simple (once you have recurrence)
- Easy to use other subproblem descriptions (e.g. vectors...)
- Only computes necessary subproblems
- Overhead of function calls
- Sometimes time complexity not obvious

Iterative DP (with table):

- More effort to code
- Need to describe subproblems with integers
- Computes always all subproblems
- Can sometimes be optimized to reuse memory
- Time complexity obvious

Drink as much as possible – Reconstruct Solution

We computed **how much** we can drink. What if we want to know **which bottles** to take?

- 1 Compute DP table or memo
- 2 Reconstruct solutions using **recurrence** and a **stack** that remembers where we come from.

Recall recurrence: $f(0) = 0$ and $f(1) = v_1$ and $f(i) = \max\{v_i + f(i-2), f(i-1)\}$

```
1    stack<int> partial; // partial solutions
2
3    void reconstruct(int i) {
4        if(i == 0) return; // p contains a solution
5        if(i == 1) partial.push(1); return; // p contains solution
6        else{
7            if(volume[i] + dp[i-2] > dp[i-1]) // we took the i-th bottle
8                partial.push(i);
9                reconstruct(i-2);
10           else // we did not take the n-th bottle
11               reconstruct(i-1);
12       }
13   }
```

Last Example: Longest Increasing Subsequence in $\Theta(n^2)$

Task: given a sequence of n integers a_1, \dots, a_n . Compute the **length** of a **longest increasing subsequence** (LIS).

First attempt: $f(i) :=$ "length of LIS in a_1, \dots, a_i ".

- Base cases: $f(0) = 0$

- $f(i) = ???$

Final attempt: $f(i) :=$ "length of LIS in a_1, \dots, a_i that ends in a_i ".

- Base cases: $f(0) = 0$

- $f(i) = \max_{j < i: a_j \leq a_i} \{1 + f(j)\}$

We had to **reformulate** the problem s.t. it admits a **recursive formulation**, this is **difficult**!

Time complexity: n function calls (with memo), i -th call takes $\Theta(i)$ time. Thus, $\Theta(n^2)$.

- Idea of DP: solve subproblems **only once** by storing solutions of subproblems
- Start by defining **recurrence relation** (on paper)
- Implement it. It will be **correct** but slow...
- Are there **overlapping subproblems**?
- **Add memo** (usually this does the trick) or construct DP table
- **Practice finding recurrence relation on paper** for well known DP problems (SubsetSum, Knapsack, Coin Change, LCS, Edit Distance, LIS...)

Brute Force Tricks

Brute force: some problems are **hard** and we only know how to solve them by **trying everything**.

However, one can often do it a **little bit smarter**:

- 1 Heuristics (important in practice, not in AlgoLab)
- 2 **Improve worst case complexity :**)

We will see a trick called **Split and List**.

This trick is why there is “DES” and “triple-DES” but no “double-DES”...

Example: SubsetSum

Task: given a set $S \subseteq \mathbb{N}$ of size n , and $k \in \mathbb{N}$. Is there a subset $S' \subseteq S$ such that $\sum_{s \in S'} s = k$?

NP complete

There is a DP solution in $\Theta(n \cdot k)$, good for small k .

Here we assume n is small and k is large and solve it with brute force.

We want to check all subsets!

- Recursive algorithm
- Iterative algorithm

SubsetSum – Recursive

Task: given a set $S = \{s_1, \dots, s_n\} \subseteq \mathbb{N}$, and $k \in \mathbb{N}$. Is there a subset $S' \subseteq S$ such that $\sum_{s \in S'} s = k$?

We want a **recursive definition** of $f(i, j) :=$ “is there $S' \subseteq \{s_1, \dots, s_i\}$ s.t. $\sum_{s \in S'} s = j$ ”

- Base cases: $f(i, 0) = \text{True}$, for all i and $f(0, j) = \text{False}$, for all $j > 0$.
- $f(i, j) = f(i - 1, j - s_i) \vee f(i - 1, j)$

Recursive algorithm:

```
1  bool f(int i, int j) {  
2      if(j == 0) return true;  
3      if(i == 0 || j != 0) return false;  
4      return f(i-1, j-elements[i]) || f(i-1, j);  
5  }
```

Time complexity: $\Theta(2^n)$, ok for $n \approx 25$

SubsetSum – Iterative

How can we iterate over all subsets of an n element set? [Trick](#): encode set in integer.

```
1  bool subsetsu(int i) {
2      for(int s = 0; s < 1<<n; ++s){ // iterate through all subsets
3          int sum = 0;
4          for(int i = 0; i < n; ++i){
5              if(s & 1<<i) sum += elements[i]; // if i-th element in subset
6          }
7          if(sum == k) return true;
8      }
9      return false;
10 }
```

Time complexity: $\Theta(n \cdot 2^n)$, ok for $n \approx 25$

Subset Sum – Faster? Split and List

Lemma: Let $S = S_1 \cup S_2$ and $S_1 \cap S_2 = \emptyset$. The following statements are equivalent:

- There is a $S' \subseteq S$ with $\sum_{s \in S'} s = k$
- There are $S'_1 \subseteq S_1$ and $S'_2 \subseteq S_2$ such that $\sum_{s \in S'_1} s + \sum_{s \in S'_2} s = k$

Idea: use second statement to check the first.

Algorithm sketch:

- **Split** S into S_1 and S_2 of size $\approx \frac{n}{2}$
- **Lists** all subset sums of S_1 and S_2 in L_1 and L_2
- Sort L_2
- For each k_1 in L_1 check if there is k_2 in L_2 such that $k_1 + k_2 = k$.

Time complexity: $\Theta(n \cdot 2^{\frac{n}{2}})$, ok for $n \approx 50$

