

Definitions:

- $n \in \mathbb{N}^+$ , the number of potions;
- $m \in \mathbb{N}$ , the total stench,  $m$  is initially 0;
- sequence  $v[1, 2, \dots, n]$ , the (initial) stench factors, where  $\forall i \in \{1, 2, \dots, n\}, v[i] \in \mathbb{Z}_{50}$  (i.e.  $\{0, 1, \dots, 49\}$ );
- function  $(, ) : \mathbb{Z}_{50} \times \mathbb{Z}_{50} \rightarrow \mathbb{Z}_{50}$ , the action of pouring potion, defined as  $(a, b) = a + b$ , here  $+$  is the addition in  $\mathbb{Z}_{50}$ ;
- sequence of evaluation should be done sequentially, i.e. we can only pour potions from adjacent one, i.e.  $(a, b)$  should only be done if  $a$  and  $b$  are numbers (in other words expressions that have already been evaluated), e.g.  $(1, (2, 3))$  should be done in the order of  $(2, 3)$  and then  $(1, 5)$ ;
- each evaluation  $(a, b)$  increments  $m$  by  $a \times b$ , here  $\times$  is the regular multiplication, i.e. the effect of pouring potion on the total stench;
- sequence of function evaluations  $F_\sigma(i, k)$  that sequentially evaluates  $(, )$  on the elements of sequence  $v[i, \dots, k]$  in a certain order, i.e. the order of pouring potion, where  $\sigma \in \mathfrak{F}(i, k)$  is some index denoting one possible way of evaluating  $v[i, \dots, k]$ , and  $\mathfrak{F}(i, k)$  is the index set for  $F_\sigma(i, k)$ , for example  $F_\mu(1, 3) = (1, (2, 3))$ , and  $F_\nu(1, 3) = ((1, 2), 3)$ , and etc;
- we notice that the value obtained from the evaluation  $F_\sigma(i, k)$  does not depend on  $\sigma$ , therefore we define  $F(i, k) = \text{value of } F_\sigma(i, k) = \sum_{l=i}^k v[l]$ ;  
 $F(i, i) := v[i]$ , which is a simple value, and no evaluation is needed;

- the minimum total stench:

$$\hat{m} = \min_{\sigma \in \mathfrak{F}(1, n)} \{m \text{ after sequence of evaluations } F_\sigma(1, n)\};$$

- the minimum total stench after pouring potions  $i$  to  $k$ :

$$\hat{m}(i, k) = \min_{\sigma \in \mathfrak{F}(i, k)} \{m \text{ created by } F_\sigma(i, k)\}, \text{ note that } \hat{m}(1, n) = \hat{m};$$

$$\hat{m}(i, i) := 0;$$

- the order of pouring potions  $i$  to  $k$ , that creates the minimum stench:

$$\hat{F}(i, k) = \operatorname{argmin}_{\sigma \in \mathfrak{F}(i, k)} \{m \text{ created by } F_\sigma(i, k)\}$$

Statement of the problem:

The aim is to develop an algorithm that,

given  $v[1, \dots, n]$ , finds  $\hat{m} = \min_{\sigma \in \mathfrak{F}(1, n)} \{m \text{ after sequence of evaluations } F_\sigma(1, n)\},$

i.e. finds the order of pouring that creates the minimum total stench.

Statement of the algorithm:

First we notice that, there is a one-one correspondence between

$\sigma \in \mathfrak{F}(i, k)$  and  $(j \geq i, \mu \in \mathfrak{F}(i, j), \nu \in \mathfrak{F}(j+1, k))$ , and, in particular,

$\forall k > i+1, \sigma \in \mathfrak{F}(i, k), \exists! j \geq i, \mu \in \mathfrak{F}(i, j), \nu \in \mathfrak{F}(j+1, k), s.t. F_\sigma(i, k) = (F_\mu(i, j), F_\nu(j+1, k))$ ,

and therefore we have:

$$\begin{aligned}
\hat{m}(i, k) &= \min_{\sigma \in \mathfrak{F}(i, k)} \{m \text{ created by } F_\sigma(i, k)\} \\
&= \min_{j, \mu, \nu} \{m \text{ created by } (F_\mu(i, j), F_\nu(j+1, k))\} \\
&= \min_{j, \mu, \nu} \{m \text{ created by } F_\mu(i, j) + m \text{ created by } F_\nu(j+1, k) + F(i, j) \times F(j+1, k)\} \\
&= \min_j \{ \min_{\mu, \nu} \{m \text{ created by } F_\mu(i, j) + m \text{ created by } F_\nu(j+1, k) + F(i, j) \times F(j+1, k)\} \} \\
&= \min_j \{ \min_{\mu} \{m \text{ created by } F_\mu(i, j)\} + \min_{\nu} \{m \text{ created by } F_\nu(j+1, k)\} + F(i, j) \times F(j+1, k) \} \\
&= \min_j \{ \hat{m}(i, j) + \hat{m}(j+1, k) + F(i, j) \times F(j+1, k) \}
\end{aligned}$$

which is the optimal substructure of the problem.

To develop an algorithm from this optimal substructure, we either

- first recursively call the function to compute  $\hat{m}(i, j)$  and  $\hat{m}(j+1, k)$ , and then iterate over  $j$  to find  $\hat{m}(i, k)$ , which describes a top-down recursive algorithm,
- or we can first compute all the  $\hat{m}(i, i)$ , then  $\hat{m}(i, i+1)$ , and then  $\hat{m}(i, i+2)$ , till  $\hat{m}(1, n)$  to get the desired solution, which describes a bottom-up algorithm.

Either way, we need to memoize/store the values of  $\hat{m}(i, j)$  that have been calculated to avoid repetitive calculation of the same value, and we also need calculate and store the values of  $F(i, j)$  beforehand to avoid repetition.

The time cost for bottom-up solution is  $\Theta(n^3)$ , and the space cost is  $\Theta(n^2)$ , there is no worst case, best case, or average case for the algorithm, since in any situation, we calculate everything.

Below is the pseudo code for the bottom-up algorithm:

The input  $v$  is a sequence (1D array), which stores the sequence  $v$  described above.

The  $m$  2D array stores  $\hat{m}(i, j)$  described above in  $m[i, j]$ , and  $m[i, i] = 0$ .

The  $f$  2D array stores the value of the function evaluation  $F(i, j)$  at  $f[i, j]$ , and  $f[i, i] = v[i]$ .

The output is  $m[1, n] = \hat{m}(1, n) = \hat{m}$ , the minimum total stench.

Algorithm Potion-Adding-Order( $v$ )

$n = v.length$

let  $m[1...n, 1...n]$  and  $f[1...n, 1...n]$  be new tables

for  $i = 1$  to  $n$

$m[i, i] = 0$

```

     $f[i, i] = v[i]$ 
    for  $j = i + 1$  to  $n$ 
         $f[i, j] = f[i, j - 1] + v[j] \bmod 50$ 
    end
end
for  $l = 2$  to  $n$ 
    for  $i = 1$  to  $n - l + 1$ 
         $j = i + l - 1$ 
         $m[i, j] = \infty$ 
        for  $k = i$  to  $j - 1$ 
             $q = m[i, k] + m[k + 1, j] + f[i, k] \times f[k + 1, j]$ 
            if  $q < m[i, j]$ 
                 $m[i, j] = q$ 
            end
        end
    end
end
return  $m[1, n]$ 

```

Argument for Optimality (for the bottom up solution):

First, I argue that no matter what method is employed, we need to find  $\hat{m}(i, k)$  for every  $i, k$ .

Suppose we did not find  $\hat{m}(i, k)$ , i.e. for  $\sigma \in \mathfrak{F}(i, k)$ , we don't know which  $\sigma$  corresponds to the  $F_\sigma(i, k)$  that produces  $\hat{m}(i, k)$ .

Then we don't know  $\min_{\sigma} \{\hat{m}(1, i - 1) + m \text{ created by } F_\sigma(i, k) + F(1, i - 1) \times F(i, k)\}$ ,

which equals  $\min_{\mu, \nu} \{m \text{ created by } F_\mu(1, i - 1) + m \text{ created by } F_\nu(i, k) + F(1, i - 1) \times F(i, k)\}$ .

Then we don't know  $\min_j \{\min_{\mu, \nu} \{m \text{ created by } F_\mu(1, j - 1) + m \text{ created by } F_\nu(j, k) + F(1, j - 1) \times F(j, k)\}\}$ ,

which equals  $\min_{\sigma \in \mathfrak{F}(i, k)} \{m \text{ created by } F_\sigma(1, k)\}$ , which is simply  $\hat{m}(1, k)$ .

By the same logic, we reason that we don't know  $\hat{m}(1, n)$ , i.e. even if we get some value, correct or not, we don't know whether it is the minimum, whether it is the answer.

Second, I argue that in finding each  $\hat{m}(i, k)$ , we need to iterate through all the values  $j$  between  $i$  and  $k$  to calculate  $\hat{m}(i, j) + \hat{m}(j + 1, k) + F(i, j) \times F(j + 1, k)$ .

Suppose we did not go through  $j_0$ , then we don't know  $\min_j \{\hat{m}(i, j) + \hat{m}(j + 1, k) + F(i, j) \times F(j + 1, k)\}$ , since this  $j_0$  we did not go through could be exactly the one that produces the above minimum. Therefore we don't know  $\hat{m}(i, k)$ .

From the argument above, we can see that we need  $\Theta(n^3)$  calculations of  $\hat{m}(i, j) + \hat{m}(j + 1, k) + F(i, j) \times F(j + 1, k)$ , for each  $i \leq j < k$ , no matter the form/implementation of the algorithm.

In our bottom-up solution which also stores all calculated  $\hat{m}(i, j)$  and  $F(i, j)$ , we have constant time cost for calculating  $\hat{m}(i, j) + \hat{m}(j + 1, k) + F(i, j) \times F(j + 1, k)$ . When we need to calculate this expression, since the lag between  $i$  and  $j$ , or  $j + 1$  and  $k$ , is less than the lag between  $i$  and  $k$ , we will have already calculated and stored the values of  $\hat{m}(i, j)$ ,  $\hat{m}(j + 1, k)$ ,  $F(i, j)$ , and  $F(j + 1, k)$ , and therefore the calculation is constant. Since the calculations are necessarily needed, and the cost for each calculation is optimal (constant), the whole algorithm is optimal.