

Solution:

(a) The algorithm is defined as follows:

def SmallestNumBills(C, B):

```
1 : if  $C = 0$ :           # Base case where the amount of currency is 0
2 :     return 0
3 : else if  $C < 0$ :       # Base case where the amount of currency is negative
4 :     return  $\infty$ 
5 : else:                # Try every possible bill
6 :     return  $1 + \min\{\text{SmallestNumBills}(C - B[1], B), \dots, \text{SmallestNumBills}(C - B[n], B)\}$ 
```

The argument C means the amount of currency, B is the set of all denominations with cardinality n , in problem 1's case, $B[1]$ represents 1, $B[2]$ represents 4, ..., $B[8]$ represents 365.

If the bill we choose is larger than the amount of currency, we simply return ∞ to ignore the situation, if C is 0, there is no choice to draw a bill, so we return 0.

Otherwise, we try every possible bill to make a sequence of decisions, and return the smallest number of bills.

(b) The worst case of this problem is obviously bounded by $\Theta(C)$, for example, we only have two denominations, one is 1, and the other is $C + 1$. A dynamic programming utilizes a 1-d array, and is defined as follows:

def SmallestNumBills(C, B):

```
1 : for  $i \leftarrow 1$  to  $C$ :
2 :      $N[i] \leftarrow \infty$ 
3 : for  $j \leftarrow 1$  to  $n$ :
4 :      $N[B[j]] \leftarrow 1$ 
5 :  $N[0] \leftarrow 0$ 
6 : for  $i \leftarrow 1$  to  $C$ :
7 :     for  $j \leftarrow 1$  to  $n$ :
8 :         if  $C - B[j] < 0$ :
9 :              $a_j \leftarrow \infty$ 
10 :        else:
11 :             $a_j \leftarrow N[C - B[j]]$ 
12 :         $N[i] \leftarrow 1 + \min\{a_1, \dots, a_n\}$ 
13 : return  $N[C]$ 
```

N is a 1-d array, in which $N[i]$ records the smallest number of bills to produce an amount of i currency. So for every possible bill $B[j]$, $N[B[j]] = 1$, which means we only need 1 bill to produce $B[j]$ currency. $N[0] = 0$, because 0 indicates no bill. Local variables a_1 to a_n indicate for every possible bill, the corresponding smallest number of bills to produce an amount of $C - B[j]$ currency, if the amount becomes negative when the bill is larger than C , we assign ∞ .

For initialization, the time complexity is $O(C + n + 1)$, for the main for-loop, the time complexity is $O(Cn)$, because the number of dominations is limited, so n is a constant, then the total time complexity is $O(C)$.

(c)

```

1 Bill = [1, 4, 7, 13, 28, 52, 91, 365]
2
3 def SmallestNumBills(n):
4     N = []
5     N.append(0)
6     for i in range(1, 366):
7         N.append(float("inf"))
8
9     for j in range(len(Bill)):
10        N[Bill[j]] = 1
11
12    if n > 365:
13        for i in range(n-365):
14            N.append(float("inf"))
15
16    A = []
17    for i in range(len(Bill)):
18        A.append(float("inf"))
19
20    for i in range(1, n+1):
21        for j in range(len(Bill)):
22            if i - Bill[j] < 0:
23                A[j] = float("inf")
24            else:
25                A[j] = N[i - Bill[j]]
26        N[i] = 1 + min(A)
27
28    return N[n]
29
30 def SmallestNumBillsGreedy(n):
31     count = 0
32     while n > 0:
33         for j in reversed(range(len(Bill))):
34             if n - Bill[j] >= 0:
35                 n -= Bill[j]
36                 count += 1
37                 break
38     return count

```

```

1 for i in range(1, 1000):
2     if SmallestNumBillsGreedy(i) != SmallestNumBills(i):
3         print(i)

```

416

Implement both algorithm in part (b) and greedy algorithm, 416 is the smallest number that the results of these two algorithms differ. Since the greedy algorithm will give us 7 bills ({365, 28, 14, 7, 1, 1, 1}) but the correct result is 5 {(91, 91, 91, 91, 52)}.

Solution:

Reference

[1] E. Demaine, L. W. Sun, and C. E. Leiserson. "Intro to Algorithms Problem Set 8 Solutions". *Massachusetts Institute of Technology*. November 14, 2001.

- Define $MinLength(i, j)$ for typesetting the i^{th} through j^{th} words as:

$$MinLength(i, j) = (j - i) + \sum_{k=i}^j l(k) \quad (1)$$

which indicates the minimum length required to fit the i^{th} through j^{th} words in a line.

- Define $LineCost(i, j)$ for typesetting the i^{th} through j^{th} words as:

$$LineCost(i, j) = \begin{cases} \infty & \text{if } MinLength(i, j) > L \\ 0 & \text{if } j = n, \text{ which indicates the last line} \\ (L - (j - i) - \sum_{k=i}^j l(k))^3 & \text{otherwise} \end{cases} \quad (2)$$

which returns ∞ if the i^{th} through j^{th} words could not be fitted in a single line, or 0 for the last line, or the slop for any line excluding the last.

- Define the value of the optimal solution in which the total slop (the sum of line slops excluding the last) is minimized as:

$$C(j) = \min\{C(i - 1) + LineCost(i, j)\}, \text{ where } 1 \leq i \leq j \quad (3)$$

where $C(j)$ denotes the value of the optimal solution of typesetting the 1^{st} through j^{th} words, we need to consider every possible way of line setting to find the optimal solution. Define $C(0) = 0$ as a base case.

- The algorithm for solving this problem is defined as follows:

We construct a 1-d array to store the values from $C(0)$ to $C(n)$. We calculate the value of each element in C from bottom to up since for every $C(j)$, every $C(k)$ (where $0 \leq k < j$) is available by the time when $C(j)$ is being computed.

To record how to divide words into lines, construct another 1-d array, P , where $P(k)$ is the value that minimizes $C(k)$, or:

$$P(k) = \operatorname{argmin}(C(k)) = \operatorname{argmin}\{C(i - 1) + LineCost(i, k)\}, \text{ where } 1 \leq i \leq k \quad (4)$$

so $P(k)$ is the i that minimizes $C(k)$.

- So after the arrays C and P are obtained, $C(n)$ is the optimal cost and the optimal solution is to print the $P(n)^{th}$ to n^{th} words in the last line, the $P(P(n) - 1)^{th}$ to $P(n - 1)^{th}$ words in the second last line, ..., and so forth.

Computing $LineCost(i, j)$ takes $O(j - i + 1)$ time, since we have to add up the length of the i^{th} to j^{th} words. But it can be optimized in $O(1)$ time by constructing a 1-d array, L , where $L(i)$ stores the cumulative sum of lengths of the 1^{st} to i^{th} words.

The time complexity of our algorithm is $O(n^2)$, since the main for-loop for computing C takes $O(n^2)$ time, this is because we should consider each i to determine the minimum cost. The space complexity is $O(n)$ since we constructs three 1-d arrays, namely, C, P, L .

■

Solution:

(a) The original $\text{EditRecursive}(S, T)$ function takes two arguments, string $S[1\dots m]$ and string $T[1\dots n]$, and returns the edit distance of S and T .

def $\text{EditRecursive}(S, T)$:

```
1 : if Length(S) = 0:      # Base case where S is empty
2 :   return Length(T) (or n)
3 : if Length(T) = 0:      # Base case where T is empty
4 :   return Length(S) (or m)
5 : DelCost ← EditRecursive(S[1...m-1], T[1...n]) + 1  # Cost of deleting one char in S
6 : InsCost ← EditRecursive(S[1...m], T[1...n-1]) + 1  # Cost of inserting one char in S
7 : if S[m] = T[n]:        # Matched case where the last char in S matches the last char in T
8 :   MatchCost ← EditRecursive(S[1...m-1], T[1...n-1])
9 : else:                  # Mismatched case where the last char in S mismatches the last char in T
10 :   MatchCost ← EditRecursive(S[1...m-1], T[1...n-1]) + 1
11 : return min{DelCost, InsCost, MatchCost}
```

In $\text{EditRecursive}(S, T)$, line 1 to line 4 solve the problem for two base cases where S or T is empty, line 5 is the cost of deleting S 's last character, line 6 is the cost of inserting a character to the end of S , line 10 is the cost of substituting $S[m]$ with $T[n]$ if $S[m]$ mismatches $T[n]$, and line 8 is the cost of DOING NOTHING if $S[m]$ matches $T[n]$.

Although the above code can handle all 5 cases correctly, I will modify it by considering if we can DO NOTHING first, because DOING NOTHING STRICTLY DOMINATES deletion, insertion, and substitution. This is easy to prove, since if $S[m]$ matches $T[n]$, the edit distance is 0 for substrings $S[m]$ and $T[n]$, we can just consider the edit distance of $S[m-1]$ and $T[n-1]$.

Therefore, I will move the statement “if $S[m] = T[n]$ ” above, such that we can reduce the number of calls by line 5 (deletion) and line 6 (insertion). The modified algorithm is as follows:

def $\text{EditRecursive}(S, T)$:

```
1 : if Length(S) = 0:
2 :   return Length(T) (or n)
3 : if Length(T) = 0:
4 :   return Length(S) (or m)
5 : if S[m] = T[n]:
6 :   MatchCost ← EditRecursive(S[1...m-1], T[1...n-1])
7 :   return MatchCost
8 : else:
9 :   DelCost ← EditRecursive(S[1...m-1], T[1...n]) + 1
```

```

10 :   InsCost  $\leftarrow$  EditRecursive( $S[1\dots m]$ ,  $T[1\dots n-1]$ ) + 1
11 :   MatchCost  $\leftarrow$  EditRecursive( $S[1\dots m-1]$ ,  $T[1\dots n-1]$ ) + 1
12 :   return min{DelCost, InsCost, MatchCost}

```

Then we can implement the modified $\text{EditRecursive}(S, T)$ function to compute the bounded edit distance, and write a function $\text{BoundedEditDist}(S, T, B)$, that takes strings S, T , and a non-negative integer B (B is valid if and only if it is non-negative, 0 means S and T are exactly the same), and returns either ∞ if the edit distance of S and T is greater than B , or the value of edit distance if it is less than or equal to B . Note that after each deletion, insertion, or substitution, we should take $B - 1$ as the third argument of our new recursive call.

def BoundedEditDist(S, T, B):

```

1 : if Length( $S$ ) = 0:
2 :     if Length( $T$ ) >  $B$ :
3 :         return  $\infty$ 
4 :     else:
5 :         return Length( $T$ )
6 : if Length( $T$ ) = 0:
7 :     if Length( $S$ ) >  $B$ :
8 :         return  $\infty$ 
9 :     else:
10 :        return Length( $S$ )
11 : if  $S[m] = T[n]$ :
12 :     MatchCost  $\leftarrow$  BoundedEditDist( $S[1\dots m-1]$ ,  $T[1\dots n-1]$ ,  $B$ )
13 :     return MatchCost
14 : else:
15 :     DelCost  $\leftarrow$  BoundedEditDist( $S[1\dots m-1]$ ,  $T[1\dots n]$ ,  $B-1$ ) + 1
16 :     InsCost  $\leftarrow$  BoundedEditDist( $S[1\dots m]$ ,  $T[1\dots n-1]$ ,  $B-1$ ) + 1
17 :     MatchCost  $\leftarrow$  BoundedEditDist( $S[1\dots m-1]$ ,  $T[1\dots n-1]$ ,  $B-1$ ) + 1
18 :     return min{DelCost, InsCost, MatchCost}

```

Reference

[1] J. Erickson. Algorithm, Chapter 3.7.

(b) I will answer this question for a more general case, such that S is of length m and T is of length n , and the bound is $O(mn)$.

We use a $(m+1) \times (n+1)$ 2-d array, $Edit$, to save the edit distances of substrings of S and T , each entry $Edit[i, j]$ represents the edit distance of $S[1\dots i]$ and $T[1\dots j]$. Entry $Edit[i, 0] = i$ which represents i deletions to convert $S[1\dots i]$ to an empty string. Entry $Edit[0, j] = j$ which represents j insertions to convert an empty string to $T[1\dots j]$.

The algorithm is as follows:

def EditDist(S, T):

```

1 : for  $j \leftarrow 0$  to  $n$ :

```

```
2:   Edit[0, j] ← j:
3: for i ← 1 to m
4:   Edit[i, 0] ← i:
5:   for j ← 1 to n:
6:     ins ← Edit[i, j − 1] + 1
7:     del ← Edit[i − 1, j] + 1
8:     if S[i] = T[j]:
9:       match ← Edit[i − 1, j − 1]
10:    else:
11:      match ← Edit[i − 1, j − 1] + 1
12:      Edit[i, j] ← min{ins, del, match}
13: return Edit[m, n]
```

The first for-loop takes $O(n)$ time, the second for-loop takes $O(mn)$ time, therefore, the algorithm is bounded by $O(mn)$ time, if S and T both have length n , then it is bounded by $O(n^2)$ time. ■