

Dynamic Programming

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Web page: <https://github.com/rossanoventurini/CompetitiveProgramming>

These notes sketch the content of 16th and 17th lectures.

1 Minimum Cost Path

► **Problem 1** (Minimum Cost Path). We are given a matrix M of $n \times m$ integers. The goal is to find the minimum cost path to move from the top-left corner to the bottom-right corner by moving only down or to right.

Consider the matrix below.

1	2	6	9
0	0	3	1
1	7	7	2

It is easy to see that the following recurrence solves the problem.

$$W(i, j) = M[i, j] + \begin{cases} 0 & \text{if } i = j = 1 \\ W(i, j - 1) & \text{if } i = 1 \text{ and } j > 1 \\ W(i - 1, j) & \text{if } i > 1 \text{ and } j = 1 \\ \min(W(i - 1, j), W(i, j - 1)) & \text{otherwise} \end{cases}$$

Thus, the problem is solved by filling a matrix W . Matrix W for the example above is as follows.

1	3	9	18
1	1	4	5
2	8	11	7

2 Longest Bitonic Subsequence

► **Problem 2** (Longest Bitonic Subsequence). Given a sequence $S[1, n]$, find the length of its longest bitonic subsequence.

A bitonic sequence is a sequence that first increases and then decreases.

Consider for example the sequence $S = 2, -1, 4, 3, 5, -1, 3, 2$. The subsequence $-1, 4, 3, -1$ is bitonic. A longest bitonic subsequence is $2, 3, 5, 3, 2$.

The idea is to compute the longest increasing subsequence from left to right and the longest increasing subsequence from right to left by using the $\Theta(n \log n)$ time solution of the previous lecture.

Then, we combine these two solutions to find the longest bitonic subsequence. This is done by taking the values in a column, adding them and subtracting one. This is correct because $\text{LIS}[i]$ computes the longest increasing subsequence of $S[1, i]$ and ends with $S[i]$.

S	2	-1	4	3	5	-1	3	2
LIS	1	1	2	2	3	1	2	2
LDS	2	1	3	2	3	1	2	1
LBS	2	1	4	3	5	1	3	2

3 Subset sum

► **Problem 3** (Subset sum). *Given a set S of n non-negative integers, and a value v , determine if there is a subset of the given set with sum equal to given v .*

The problem has a solution which is almost the same as 0/1 knapsack problem.

As in the 0/1 knapsack problem, we construct a matrix W with $n + 1$ rows and $v + 1$ columns. Here the matrix contains booleans.

Entry $W[i][j]$ is true if and only if there exists a subset of the first i items with sum j .

The entries of the first row $W[0][j]$ are set to false while entries of the first column $W[i][0]$ are set to true.

Entry $W[i][j]$ is true either if $W[i - 1][j]$ is true or $W[i - 1][j - S[i]]$ is true.

As an example, consider the set $S = \{3, 2, 5, 1\}$ and value $v = 6$. Below the matrix W for this example.

	0	1	2	3	4	5	6
0	T	F	F	F	F	F	F
3	T	F	F	T	F	F	F
2	T	F	T	T	F	T	F
5	T	F	T	T	F	T	F
1	T	T	T	T	T	T	T

4 Coin change

► **Problem 4** (Coin change). *We have n types of coins available in infinite quantities where the value of each coin is given in the array $C = [c_1, c_2, \dots, c_n]$. The goal is find out how many ways we can make the change of the amount K using the coins given.*

For example, if $C = [1, 2, 3, 8]$, there are 3 ways to make $K = 3$, i.e., 1, 1, 1, 1, 2 and 3.

The solution is similar to the one for subset sum.

The goal is to build a $(n + 1) \times (K + 1)$ matrix W , i.e., we compute the number of ways to change any amount smaller than or equal to K by using coins in any prefix of C .

The easy cases are when $K = 0$. We have just one way to change this amount. Thus, the first column of W contains 1 but $W[0, 0] = 0$ which is the number of ways to change 0 with no coin.

Now, for every coin we have an option to include it in the solution or exclude it.

If we decide to include the i th coin, we reduce the amount by coin value and use the subproblem solution $(K - c[i])$.

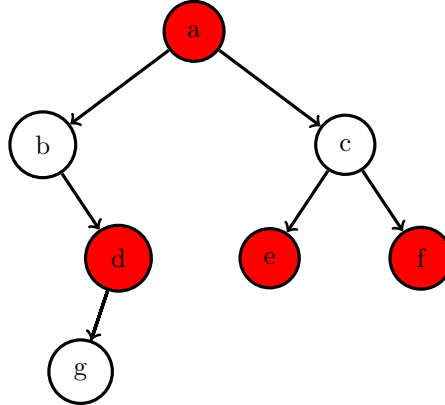
If we decide to exclude the i th coin, the solution for the same amount without considering that coin is on the entry above.

5 Largest independent set on trees

► **Problem 5** (Largest independent sets on trees). *Given a tree T with n nodes, find one of its largest independent sets.*

An independent set is a set of nodes I such that there is no edge connecting any pair of nodes in I .

Example below shows a tree whose largest independent set consists of the red nodes a, d, e, and f.



In general the largest independent set is not unique. For example, we can obtain a different largest independent set by replacing nodes a and d with nodes b and g.

Consider a bottom up traversal of the tree T . For any node u , we have two possibilities: either add or not add the node u to the independent set.

In the former case, u 's children cannot be part of the independent set but its grandchildren could. In the latter case, u 's children could be part of the independent set.

Let $\text{LIST}(u)$ be the size of the independent set of the subtree rooted at u and let C_u and G_u be the set of children and the set of grandchildren of u , respectively.

Thus, we have the following recurrence.

$$\text{LIST}(u) = \begin{cases} 1 & \text{if } u \text{ is a leaf} \\ \max(1 + \sum_{v \in G_u} \text{LIST}(v), \sum_{v \in C_u} \text{LIST}(v)) & \text{otherwise} \end{cases}$$

The problem is, thus, solved with a post-order visit of T in linear time.

Observe that the same problem on general graphs is NP-Hard.

6 Edit distance

► **Problem 6** (Edit distance). *Given two strings $S_1[1, n]$ and $S_2[1, m]$, find the minimum number of edit operations required to transform S_1 into S_2 . There are three edit operations:*

- *Insert a symbol at a given position*
- *Replace a symbol at a given position*
- *Delete a symbol at a given position*

For example, if the two strings are $S_1 = \text{hello}$ and $S_2 = \text{hallo}$, the edit distance is 1 as we can replace symbol **e** with **a** in second positions of S_1 .

Let $\text{ED}(i, j)$ be the edit distance of prefixes $S_1[1, i]$ and $S_2[1, j]$. The idea is to compute $\text{ED}(i, j)$ by using shorter prefixes as subproblems. Indeed, if $S[i] = S[j]$, $\text{ED}(i, j) = \text{ED}(i - 1, j - 1)$. We can compute $\text{ED}(i, j)$

Thus, the recurrence is as follows.

$$\text{ED}(i, j) = \begin{cases} i & \text{if } j = 0 \\ j & \text{if } i = 0 \\ \text{ED}(i - 1, j - 1) & \text{if } S[i] = S[j] \\ 1 + \min(\text{ED}(i, j - 1), \text{ED}(i - 1, j), \text{ED}(i - 1, j - 1)) & \text{otherwise} \end{cases}$$

Here we report the matrix obtained for the strings $S_1 = \text{agced}$ and $S_2 = \text{abcdef}$.

		a	b	c	d	e	f
	0	1	2	3	4	5	6
a	1	0	1	2	3	4	5
g	2	1	1	2	3	4	5
c	3	2	2	1	2	3	4
e	4	3	3	2	2	2	3
d	5	4	4	3	2	3	3

7 Longest palindromic subsequence

► **Problem 7** (Longest palindromic subsequence). *Given a sequence $S[1, n]$, find the length of its longest palindromic subsequence.*

Given sequence is $S = \text{bbabcbcab}$, then the output should be 7 as **babcbab** is the longest palindromic subsequence in it. **bbbbbb** and **bbcbb** are also palindromic subsequences of S , but not the longest ones.

Let $\text{LPS}(i, j)$ be the length of the longest palindromic subsequence of $S[i, j]$.

There is a very easy solution which reduces to the Longest Common Subsequence Problem. Indeed, it is easy to see that the longest common subsequence of S and S^R , i.e., S reversed, is the longest palindromic subsequence in S .

A direct computation of the longest palindromic subsequence is based on the idea of computing $\text{LPS}(i, j)$ by using three subproblems. If $S[i]$ and $S[j]$ equal, then we can extend the longest palindromic subsequence of $S[i + 1, j - 1]$ by prepending and appending character $S[i]$. If this is not the case, then the longest palindromic subsequence is the longest palindromic subsequence of either $S[i + 1, j]$ or $S[i, j - 1]$.

Thus, the recurrence is as follows.

$$\text{LPS}(i, j) = \begin{cases} 0 & \text{if } i > j \\ 1 & \text{if } i = j \\ 2 + \text{LPS}(i + 1, j - 1) & \text{if } S[i] = S[j] \\ \max(\text{LPS}(i + 1, j), \text{LPS}(i, j - 1)) & \text{otherwise} \end{cases}$$

Here we report the matrix obtained for the example above. Observe that we have to fill the matrix starting from its diagonal

	b	b	a	b	c	b	c	a	b
b	1	2	2	3	3	5	5	5	7
b	0	1	1	3	3	3	3	5	7
a	0	0	1	1	1	3	3	5	5
b	0	0	0	1	1	3	3	3	5
c	0	0	0	0	1	1	3	3	3
b	0	0	0	0	0	1	1	1	3
c	0	0	0	0	0	0	1	1	1
a	0	0	0	0	0	0	0	1	1
b	0	0	0	0	0	0	0	0	1

8 Weighted job scheduling

► **Problem 8** (Weighted job scheduling). *There are n jobs and three arrays $S[1 \dots n]$ and $F[1 \dots n]$ listing the start and finish times of each job, and $P[1 \dots n]$ reporting the profit of completing each job. The task is to choose a subset $X \subseteq \{1, 2, \dots, n\}$ so that for any pair $i, j \in X$, either $S[i] > F[j]$ or $S[j] > F[i]$, which maximizes the total profit.*

We already solved this problem (called activity selection) under the hypothesis that all the jobs have the same profit. For that easier problem, a greedy algorithm finds the optimal schedule in $\Theta(n \log n)$ time.

Consider the following example. Arrays are $S = [1, 2, 4, 6, 5, 7]$, $F = [3, 5, 6, 7, 8, 9]$, and $P = [5, 6, 5, 4, 11, 2]$.

The solution is as follows. We first sort the jobs by finish time.

Let $\text{WJS}(i)$ be the maximum profit by selecting among the first i jobs (ordered by finish time).

The value of $\text{WJS}(i)$ is computed by either excluding or including i th job. If we exclude i th job, then $\text{WJS}(i) = \text{WJS}(i - 1)$. Instead, if it is included, then we have to find the largest index of j such that $F[j] \leq S[i]$ so that $\text{WJS}(i) = \text{WJS}(j) + P[i]$. Obviously, among these two possibilities, we take the one that give the largest profit.

We assume we have a fake job with index 0 whose finish time is $-\infty$. We also let $\text{WJS}(0)$ to be 0. This serves as sentinel to avoid special cases.

Observe that sorting by finish time guarantees that if we current job i does not overlap with j th job, then it does not overlap with any other job with a smaller index. This means that we can safely use the value $\text{WJS}(j)$.

6 Dynamic Programming

Notice that the index j can be found in $\Theta(\log n)$ time with binary search. Thus, the algorithm runs in $\Theta(n \log n)$ time.

S	-	1	2	4	6	5	7
F	$-\infty$	3	5	6	7	8	9
P	0	5	6	5	4	11	2
R	0	5	6	10	14	17	17