

Dynamic Programming

ACM Seminar in Algorithmics

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Problem: Longest Increasing Subsequence

Input: A list of numbers, a_1, a_2, \dots, a_n .

Output: Find the largest k for which there are indices i_1, i_2, \dots, i_k with $a_{i_1} < a_{i_2} < \dots < a_{i_k}$.

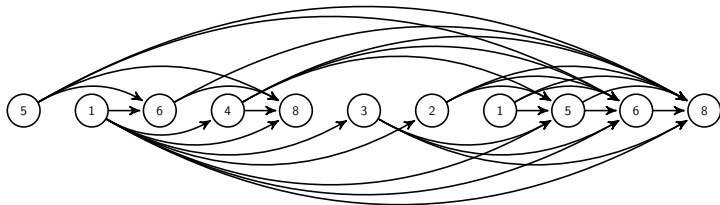
Exercise: What is the longest increasing subsequence in the following list of numbers?

5, 1, 6, 4, 8, 3, 2, 1, 5, 6, 8

Problem: Longest Increasing Subsequence

On the first sight it may seem a bit difficult to come up with a solution but as we will see there is *an underlying structure* in the problem that allows us to solve it "fast".

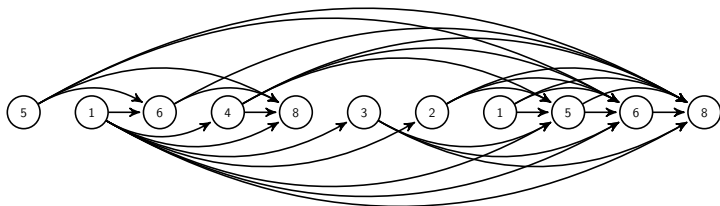
If you are faced with the following



can you tell what the underlying structure is and what its properties are?

Problem: Longest Increasing Subsequence

Let $G = (V, E)$ is a directed graph with vertices v_1, v_2, \dots, v_n which are labelled with the numbers from the list a_1, a_2, \dots, a_n . There is an edge $(v_i, v_j) \in E$ iff the corresponding numbers satisfy $a_i < a_j$.



Two important things to notice:

- The graph G is a directed acyclic graph, so-called DAG.
- There is one-to-one correspondence between paths in the graph G and the increasing subsequences in the list a_1, a_2, \dots, a_n .

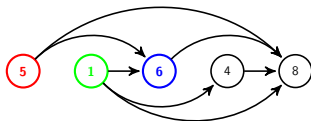
Problem: Longest Increasing Subsequence

Solution: Let us denote the length of a longest path ending in the vertex v_i as $L(i)$. Then the following algorithm computes $L(i)$ for every $i \in \{1, \dots, n\}$:

```
for  $j \leftarrow 1$  to  $n$  do  
     $L(j) \leftarrow 1 + \max\{L(i) \mid (i, j) \in E(G)\}$   
end  
return  $\max_{i=1}^n L(i)$ 
```

Example:

$$L(3) = 1 + \max\{L(1), L(2)\}$$



Dynamic Programming "Definition"

Dynamic programming is a problem solving technique based upon the following two principles:

- 1 Identification of subproblems.
- 2 Using the answer to "smaller" subproblems to solve the "bigger" ones.

In the case of the *Longest Increasing Subsequence* we have according to these principles:

- 1 $L(i)$ - the length of the longest increasing subsequence ending with a_i .
- 2 $L(i) \leftarrow 1 + \max_{j < i} \{L(j) \mid a_j < a_i\}$.

When Does Dynamic Programming Work?

A problem is solvable with dynamic programming if it has:

- ① Optimal substructure. *An optimal solution of the whole problem can be build out of optimal solutions to its subproblems.*
- ② Overlapping subproblems.

Remember, when you are faced with a DP problem the DAG is *implicit* - you are the one to define the vertices (subproblems) and the edges (relations) between them.

How do we find out a given problem is solvable using DP?

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How do we find out a given problem is solvable using DP?

Through Experience!

Problem: **Maximum Subarray Problem**

Input: An array of numbers, a_1, a_2, \dots, a_n .

Output: Find a continuous subarray within the given array which has the largest sum.

Solution:

Problem: Maximum Subarray Problem

Input: An array of numbers, a_1, a_2, \dots, a_n .

Output: Find a continuous subarray within the given array which has the largest sum.

Solution:

- 1 Subproblems: $S[i]$ - the largest sum of a subarray ending at i -th element (inclusive).
- 2 Induction: $S[i] \leftarrow a_i$ **if** $S[i - 1] \leq 0$ **else** $a_i + S[i - 1]$.

Problem: Longest Common Subsequence

Input: Two strings $a_1a_2 \cdots a_n$ and $b_1b_2 \cdots b_m$.

Output: The largest k for which there are indices

$$1 \leq i_1 < i_2 < \cdots < i_k \leq n$$

and

$$1 \leq j_1 < j_2 < \cdots < j_k \leq m$$

with

$$a_{i_1}a_{i_2} \cdots a_{i_k} = b_{j_1}b_{j_2} \cdots b_{j_k}.$$

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Solution:

- 1 Subproblems: $S[i][j]$ - the longest common subsequence of the prefixes of the two strings $a_1a_2 \cdots a_i$ and $b_1b_2 \cdots b_j$.
- 2 Induction: ($\text{diff}(a, b)$ is 1 if $a = b$ else 0)
 $S[i][j] \leftarrow \max\{S[i-1][j], S[i][j-1], S[i-1][j-1] + \text{diff}(a_i, b_j)\}.$

Problem: Knapsack Problem

Input: A list of items with their weights w_1, w_2, \dots, w_n and costs c_1, c_2, \dots, c_n , a total weight W the knapsack can hold (capacity).

Output: A subset of items for which the sum of their costs is maximum and the knapsack can hold them, i.e. $I \subseteq \{1, 2, \dots, n\}$ such that $\sum_{i \in I} c_i$ is maximum and $\sum_{i \in I} w_i \leq W$.

Solution:

Problem: Knapsack Problem

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Solution:

- 1 Subproblems: $C[\hat{w}][i]$ - the maximum achievable value of the items from a set $\{1, 2, \dots, i\}$ with the knapsack capacity \hat{w} .
- 2 Induction: $C[\hat{w}][i] = \max\{C[\hat{w}][i - 1], C[\hat{w} - w_i][i - 1] + c_i\}$
if $\hat{w} \geq w_i$ else $C[\hat{w}][i - 1]$.

Top-Down vs. Bottom-up Approach

Consider the knapsack problem again. The following solution of it is referred to as *the bottom-up approach*:

```
for  $i \leftarrow 0$  to  $n$  do
     $C[0][i] \leftarrow 0$ 
end

for  $\hat{w} \leftarrow 0$  to  $W$  do
     $C[\hat{w}][0] \leftarrow 0$ 
end

for  $i \leftarrow 1$  to  $n$  do
    for  $\hat{w} \leftarrow 1$  to  $W$  do
        if  $\hat{w} < w_i$  then
             $C[\hat{w}][i] \leftarrow C[\hat{w}][i - 1]$ 
        else
             $C[\hat{w}][i] \leftarrow C[\hat{w} - w_i][i - 1] + c_i$ 
        end
    end
end

return  $C[W][n]$ 
```

Top-Down vs. Bottom-up Approach

Now consider the following which is referred to as *the top-down approach*:

```
function solve( $\hat{w}$ ,  $i$ )
    if  $C[\hat{w}][i] = -1$  then
        if  $\hat{w} \geq w_i$  then
             $C[\hat{w}][i] \leftarrow \text{solve}(\hat{w} - w_i, i - 1) + c_i$ 
        end
         $C[\hat{w}][i] \leftarrow \max\{C[\hat{w}][i], \text{solve}(\hat{w}, i - 1)\}$ 
    end
    return  $C[\hat{w}][i]$ 
end

for  $\hat{w} \leftarrow 0$  to  $W$  do
    for  $i \leftarrow 0$  to  $n$  do
         $C[\hat{w}][i] \leftarrow -1$ 
    end
end

return solve( $W, n$ )
```

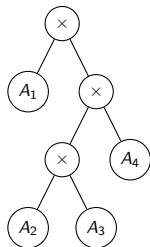

Problem: Chain Matrix Multiplication

Input: An expression $A_1 \times A_2 \times \cdots \times A_n$, where the A_i 's are matrices with dimensions $m_0 \times m_1, m_1 \times m_2, \dots, m_{n-1} \times m_n$.

Output: A parenthesization of the expression such that the number of multiplications needed to be done in order to evaluate it is minimum.

Hint:

$$A_1 \times ((A_2 \times A_3) \times A_4)$$



Problem: Chain Matrix Multiplication

Solution:

- 1 Subproblems: $C[i][j]$ - the minimum number of multiplications to evaluate $A_i \times A_{i+1} \times \cdots \times A_j$.
- 2 Induction: $C[i][j] \leftarrow \min_{i \leq k < j} \{ C[i][k] + C[k][j] + m_{i-1} \cdot m_k \cdot m_j \}$.

DP Problem Complexities

The problems that have been presented are typical representants of the following complexity classes:

$O(n)$ *Maximum Subarray Sum*

$O(mn)$ *Longest Common Subsequence*

$O(n^3)$ *Chain Matrix Multiplication*