

DYNAMIC PROGRAMMING

- Dynamic programming is a technique for solving problems with overlapping subproblems.
- Typically, these subproblems arise from a recurrence relating a solution to a given problem with solution to its smaller subproblems of the same type.
- Dynamic programming suggests solving each smaller subproblem once and recording the results in a table from which a solution to the original problem can be obtained.
- Dynamic programming = Recursion + Common Sense.
= memoization [remembering results of a few states]

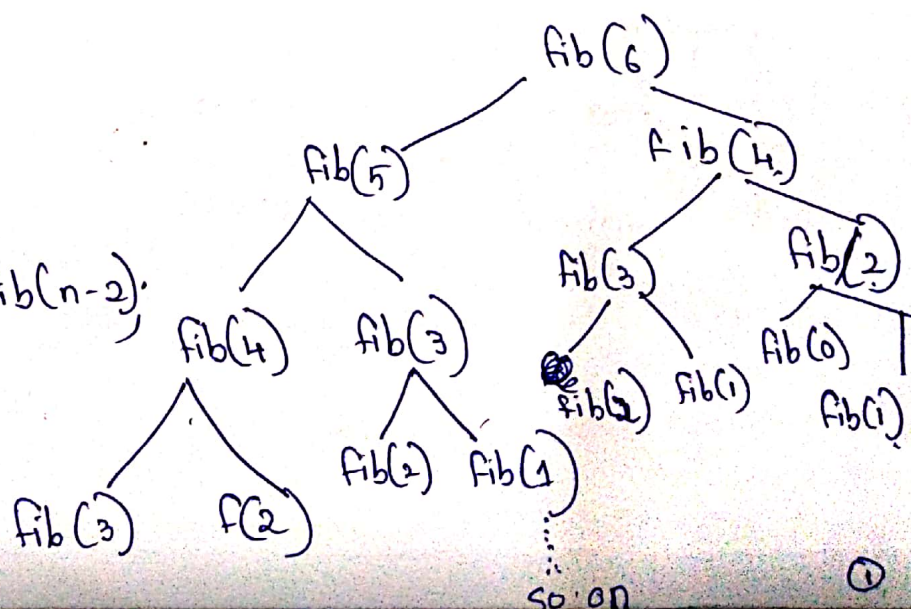
Eg: the Fibonacci Series.

pure recursion.

```
if fib(int n)
{
    if (n <= 2)
        return 1;
    return fib(n-1) + fib(n-2);
}
```

3.

trace :: fib(6).



$\text{fib}(i)$ is calculated multiple times in recursion method.

Time complexity : $O(2^n)$.

dynamic programming (adding memory to recursion method)

void fib().

{

fibresult[0] = 1;

fibresult[1] = 1;

for(int i=2; i<n; i++).

fibresult[i] = fibresult[i-1] + fibresult[i-2];

}

Time complexity = $O(n)$, space complexity = $O(n)$

• Two major properties of Dynamic programming :

→ to decide whether a problem can be solved by applying dynamic programming we have to check two properties.

(a) overlapping sub-problems

(b) optimal substructure.

(a) Overlapping sub-problems.

- suggests that the subproblem needs to be solved again and again.
- In recursion we solve those problems ~~q~~ every time. Eg: fibonacci with pure recursion method.
- In dynamic programming we solve these subproblems only once and store it for future use.
Eg: Fibonacci with dynamic programming.

(b) Optimal Substructure.

- If a problem can be solved using the solutions of the sub problems then we say that problem has a Optimal Substructure Property.

• Dynamic Programming Approaches:

(a) Bottom-up approach. [Tabular]

- suppose we need to solve the problem for N , we start solving the problem with the smallest possible inputs and store it for future.
- Now as you calculate for the bigger values use the stored solutions (solution for smaller problems).

(b) Top-down approach. [memoization]

- Break the problem into sub-problem and solve them as needed and store the solution for future.

Problems on DP (Dynamic programming) Approach.

- 1) 0/1 Knapsack.
- 2) Warshall's Algorithm. [all possible paths]
- 3) Floyd Warshall Algorithm [all pairs shortest distances]
- 4) Longest common subsequence.

NOTE: Examples for all the above have been done in class. Refer class notes.

① 0/1 KNAPSACK.

I Algorithm for 0/1 knapsack.

$$v[i, wt] = \max \{ v[i-1, wt], v[i-1, w - wt[i]] + p[i] \}$$

II Time complexity = $O(2^n)$

② WARSHALL'S ALGORITHM.

I Algorithm for Warshall's
Input: Adjacency matrix A of a directed graph with ' n ' vertices.

Output: The transitive closure of the directed graph.

$$R^{(0)} \leftarrow A.$$

for $k \leftarrow 1$ to n do.

for $i \leftarrow 1$ to n do.

for $j \leftarrow 1$ to n do.

$$R^{(k)}[i, j] \leftarrow R^{(k-1)}[i, j] \text{ or}$$

$$R^{(k-1)}[i, k] \text{ and } R^{(k-1)}[k, j]$$

Return $R^{(n)}$.

II Time complexity.

$$\text{Time complexity} = \theta(n^3).$$

③ FLOYD WARSHALL ALGORITHM.

I Algorithm.

Input: The weight matrix w of a graph with.

no negative length cycle. ^{cycle with weights that sum to negative}

Output: The distance matrix of the shortest path's number length.

$D \leftarrow W$

for $k \leftarrow 1$ to n do.

for $i \leftarrow 1$ to n do.

for $j \leftarrow 1$ to n do.

$D[i, j] \leftarrow \min \{ D[i, j], D[i, k] + D[k, j] \}$

return D .

II Time complexity.

Time complexity = $\Theta(n^3)$.

④ LONGEST COMMON SUBSEQUENCE.

I Algorithm.

if $(A[i] = B[j])$.

$LCS[i, j] = 1 + LCS[i-1, j-1]$

else.

$LCS[i, j] = \max \{ LCS[i-1, j], LCS[i, j-1] \}$

II Time complexity = $\Theta(mn)$ Space complexity = $\Theta(mn)$

0/1 knapsack problems.

1)

wt pt.

2

1

3

2

3

5

4

9

6

4

capacity = 10.

2).

wt

pt.

3

100

2

20

4

60

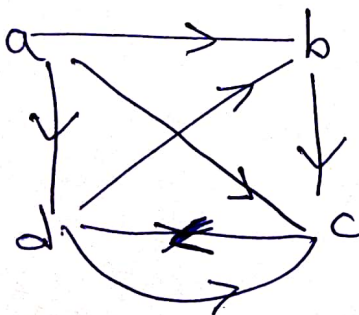
1

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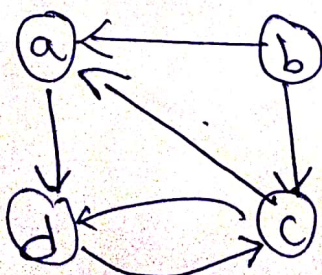
capacity = 5

Warshall's Algorithm problems

1)

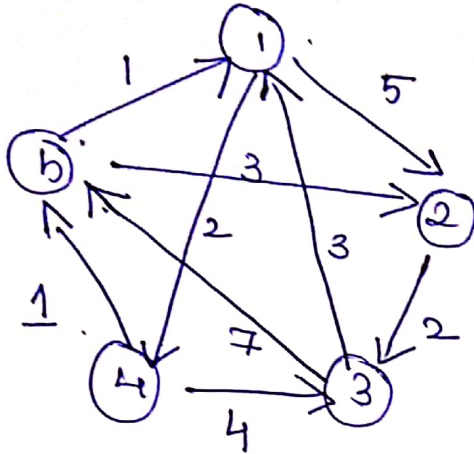


2)

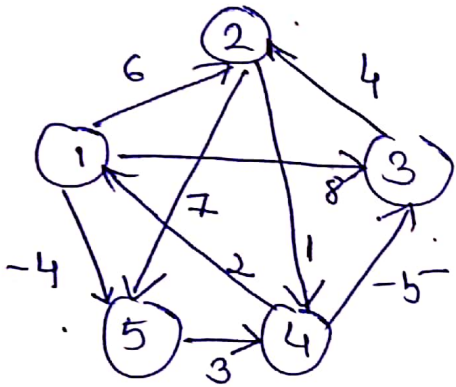


Floyd Warshall algorithm Problems

1)



2)



Longest common subsequence Problems

1)

A - stone

B - longest

2)

A - lesson

B - learnt

3)

A - Engineer

B - Edition