Dynamic Programming

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What is Dynamic programming?

- It is algorithm design technique where the subproblems of the same form occurs many time.
- We store the result and use it to avoid re-computation of subproblems repeatedly encountered in getting solution to original problem.
- It is mostly used for optimization problems, problems where multiple solutions are there and we have to opt for best solution (define optimization problem, linear and non linear programming)
- Storing the results of subproblems and using the tabulated/stored results of them is key feature of dynamic programming.

Dynamic programming-general strategy

- Dynamic programming, like the divide-and-conquer method, solves problems by combining the solutions to subproblems.
- "Programming" in this context refers to a tabular method.
- divide-and-conquer algorithms partition the problem into disjoint subproblems, solve the subproblems recursively, and then combine their solutions to solve the original problem.
- In contrast, dynamic programming applies when the subproblems <u>overlap</u>—that is, <u>when subproblems share</u> <u>subsubproblems</u>. In this context, a divide-and-conquer algorithm does more work than necessary, repeatedly solving the common subsubproblems.
- A dynamic-programming algorithm solves each subsubproblem just once and then saves its answer in a table, thereby avoiding the work of recomputing the answer every time it solves each subsubproblem.

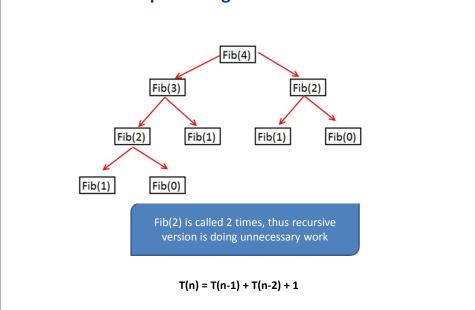
Dynamic programming-general strategy

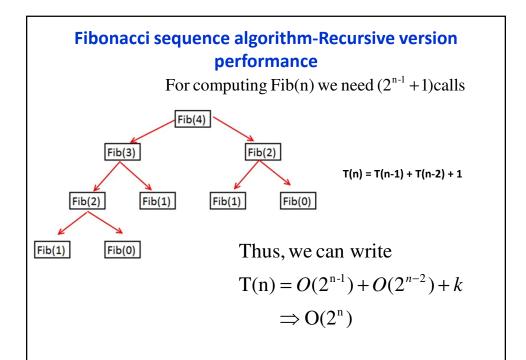
- We typically apply dynamic programming to *optimization problems*. Such problems can have many possible solutions.
 Each solution has a value, and we wish to find a solution with the optimal (minimum or maximum) value.
- When developing a dynamic-programming algorithm, we follow a sequence of four steps:
- 1. Characterize the structure of an optimal solution.
- 2. Recursively define the value of an optimal solution.
- 3. **Compute** the value of an optimal solution, typically in a **bottom-up fashion.**
- 4. **Construct** an optimal solution from computed information

Fibonacci sequence algorithm-Recursive version

```
Int FibRec (int n)
{
    if (n==0)
        return 0;
    if(n==1)
        return 1;
    else
        f=FibRec(n-1)+FibRec(n-2);
        return f;
}
F={0,1,1,2,3,5,8,13,......}
Given F(0)=0 and F(1)=1
F(n)=F(n-1)+F(n-2)
return f;
```

Fibonacci sequence algorithm-Recursive version





Fibonacci sequence algorithm- Dynamic prog.

```
Int FibDP(int n)
{
  int Fib[n+1]; //array of n+1
  Fib[0]=0; Fib[1]=1; //base
  for i=2 to n
    Fib[i]=Fib[i-1]+Fib[i-2];
  return Fib[n];
```

}

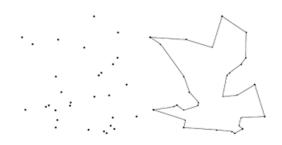
- Fib[] is an array of size n+1
- At each iteration i ,previous 2 values (i-1) and (i-2) are added
- O(n) time and space complexity

Recursive	Dynamic Programming
Time exponential O(2^n)	Time linear O(n)
Space O(2^n)	Space O(n)

https://algorithms.tutorialhorizon.com/introduction-to-dynamic-programming-fibonacci-series/

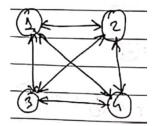
Travelling salesman Problem- Dynamic prog.

A salesman has to visit set of n cities. Each city
has to be visited only once and has to return
to the same starting city, such that the
distance travelled should be minimum.



Travelling salesman Problem (TSP)- Dynamic prog.

• The dynamic programming approach is to solve the smaller subproblems first and use their stored solutions to get solutions for bigger problems, there by avoiding the repeated computations.

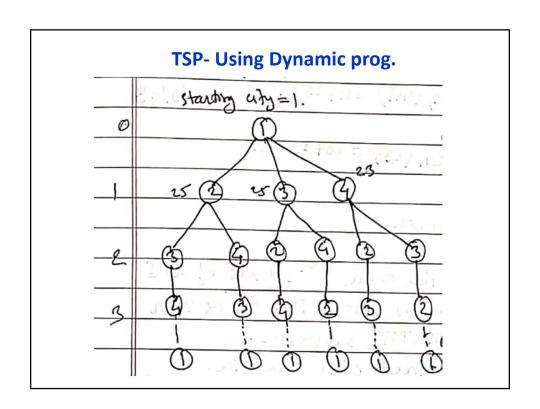


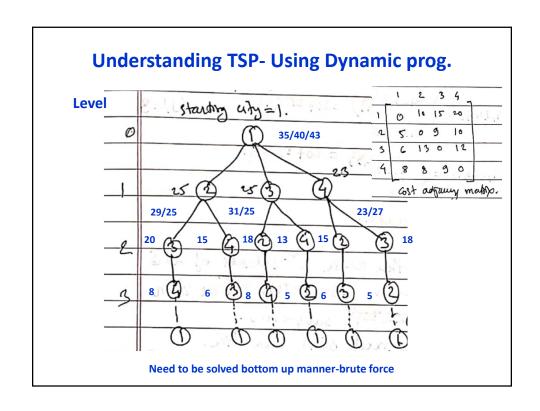
١	1	2	3 4	-
1	O	10 1	5 20	1121
2	5.	0 9	10	
3	6	13	12	
4	8	8	9 0	

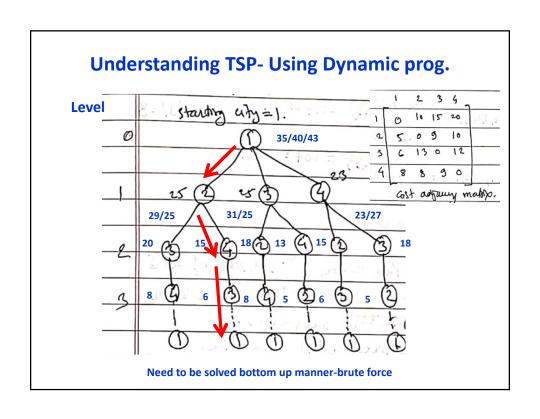
Matrix C

Travelling salesman Problem (TSP)- Dynamic prog.

- Way of working/understanding
 - Will solve by using brute-force
 - Derive the formula
 - Apply the formula







 Lets generate formula for the above problem and then we will generalize it to any starting node.

$$g(1,\{2,3,4\}) = \min \begin{cases} C_{1,2} + g(2,\{3,4\}) \\ C_{1,3} + g(3,\{2,4\}) \\ C_{1,4} + g(4,\{2,3\}) \end{cases}$$

 $g(1,\{2,3,4\})$ - cost of going from node 1 and visiting each of the node from set $s=\{2,3,4\}$ once and returning back to node 1.

$$g(2,\{3,4\}) = \min \begin{cases} C_{2,3} + g(3,\{4\}) \\ C_{2,4} + g(4,\{3\}) \end{cases}$$

$$g(3,\{2,4\}) = \min \begin{cases} C_{3,2} + g(2,\{4\}) \\ C_{3,4} + g(4,\{2\}) \end{cases}$$
$$g(4,\{2,3\}) = \min \begin{cases} C_{4,2} + g(2,\{3\}) \\ C_{4,3} + g(3,\{2\}) \end{cases}$$
$$g(3,\{4\}) = C_{3,4} + g(4,\phi)$$

 $g(4, \phi)$ – cost of going from 4 through each node in empty set and returning to node 1, which is same as $C_{4,1}$

$$g(4,{3}) = C_{4,3} + g(3,\phi)$$

$$g(i, S) = \min_{j \in S} \{ c_{ij} + g(j, S - \{j\}) \}$$

where

g(i,S)- is the shortest path starting from i and going through all the vertices in set S and terminate at node i.

https://www.youtube.com/watch?v=XaXsJJh-Q5Y

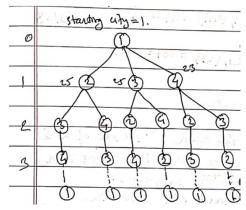
Understanding TSP- Using Dynamic prog.

Starting from level 3 compute the costs, there are links between each of the node 2,3,4 to the city 1.

$$g(2, \phi) = c_{21} = 5$$

$$g(3, \phi) = c_{31} = 6$$

$$g(4, \phi) = c_{41} = 8$$

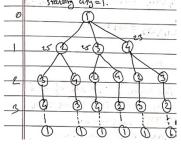


$$g(i,S) = \min_{j \in S} \left\{ c_{ij} + g(j,S - \{j\}) \right\}$$

 $g(2, \phi)$ - means there are no intermediate nodes bet 2 and 1

Computing costs at level 2

$$g(i, S) = \min_{j \in S} \left\{ c_{ij} + g(j, S - \{j\}) \right\}$$



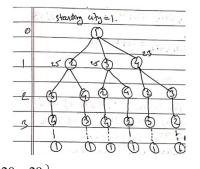
$g(2,{3}) = c_{23} + g(3,\phi) = 9 + 6 = 15$
$g(2,{4}) = c_{24} + g(4,\phi) = 10 + 8 = 18$
$g(3,{2}) = c_{32} + g(2,\phi) = 13 + 5 = 18$
$g(3,{4}) = c_{34} + g(4,\phi) = 12 + 8 = 20$
$g(4,{3}) = c_{43} + g(3,\phi) = 9 + 6 = 15$
$g(4,{2}) = c_{42} + g(2,\phi) = 8 + 5 = 13$

1	1	2	3	4 _	
1	O	10	12	20	1. 5. 4
2	5.	. 0	9	10	
3	6	13	0	12	
4	8	8	. 9	٥	1

Understanding TSP- Using Dynamic prog.

Computing costs at level 1

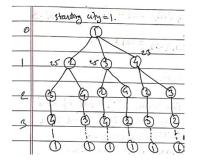
$$g(i, S) = \min_{j \in S} \left\{ c_{ij} + g(j, S - \{j\}) \right\}$$



$$\begin{split} g(2,\{3,4\}) &= \min \begin{cases} j=3 & c_{23} + g(3,\{4\}) = 9 + 20 = 29 \\ j=4 & c_{24} + g(4,\{3\}) = 10 + 15 = 25 \end{cases} \\ g(2,\{3,4\}) &= 25 \\ g(3,\{2,4\}) &= \min \begin{cases} j=2 & c_{32} + g(2,\{4\}) = 13 + 18 = 31 \\ j=4 & c_{34} + g(4,\{2\}) = 12 + 13 = 25 \end{cases} \\ g(3,\{2,4\}) &= 25 \end{split}$$

Computing costs at level 1

$$g(i, S) = \min_{j \in S} \left\{ c_{ij} + g(j, S - \{j\}) \right\}$$

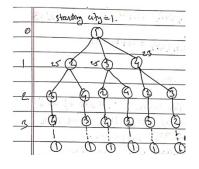


$$g(4,\{2,3\}) = \min \begin{cases} j = 2 & c_{42} + g(2,\{3\}) = 8 + 15 = 23 \\ j = 3 & c_{43} + g(3,\{2\}) = 9 + 18 = 27 \end{cases}$$
$$g(4,\{2,3\}) = 23$$

Understanding TSP- Using Dynamic prog.

Computing costs at level 0

$$g(i, S) = \min_{j \in S} \left\{ c_{ij} + g(j, S - \{j\}) \right\}$$

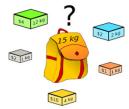


$$g(1,\{2,3,4\}) = \min \begin{cases} j = 2 & c_{12} + g(2,\{3,4\}) = 10 + 25 = 35 \\ j = 3 & c_{13} + g(3,\{2,4\}) = 15 + 25 = 40 \\ j = 4 & c_{14} + g(4,\{2,3\}) = 20 + 23 = 43 \end{cases}$$

 $g(1,\{2,3,4\}) = 35$

Final answer

0/1 knapsack problem



- We have a knapsack with a capacity of weight W and a set of objects with their corresponding profits. We have to choose the set of objects with weights <=W and has to maximize the profit.
- 0/1 means we can either pick an object (1) or not pick(0) it. That is **partial object** is not allowed.
- An object can be picked only once.

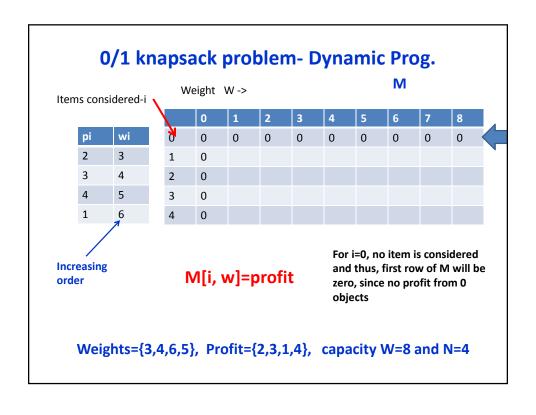
0/1 knapsack problem

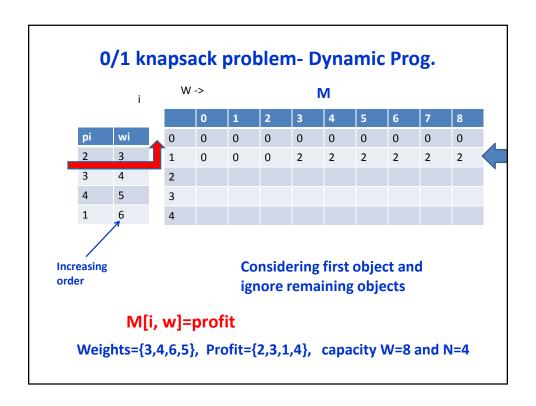
Object	ob1	ob2	ob3
weight	2	4	8
profit	20	25	60

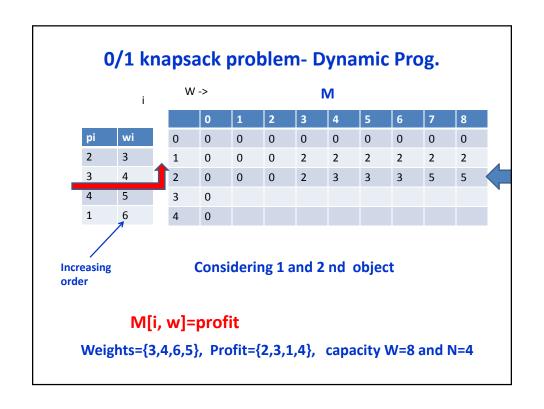
Given knapsack capacity M=12, find the objects to be put in the sack to get maximum profit with weight<=12

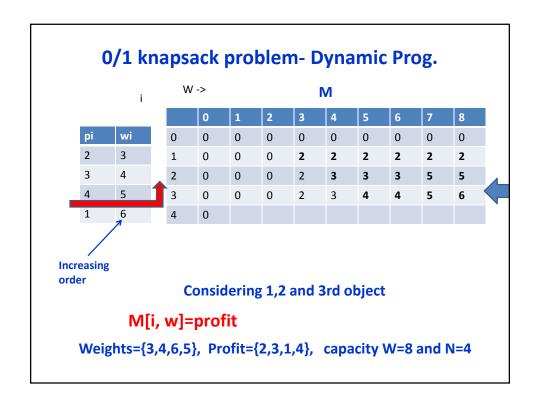
For each object two possibilities are there 1 or 0. Thus, for n objects we have 2ⁿ possibilities.

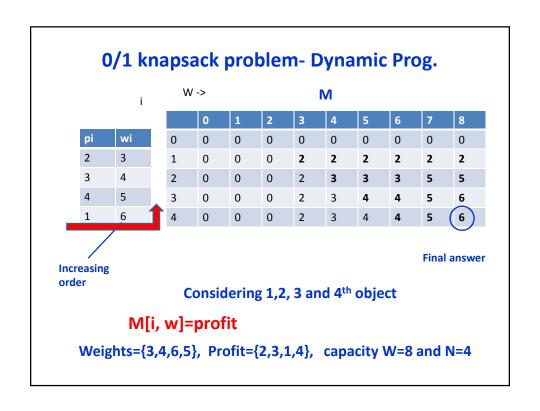
	Object	ob1	ob2	ob3	
	weight	2	4	8	
	profit	20	25	60	
o	bjects	Weight	profit		
	000	0	0		
	001	8	60		
	010	4	25		
	011	12	85		
	100	2	20		
	101	10	80		
	110	6	45		
	111	14 >12			
		(not possible)			











0/1 knapsack problem- Dynamic Prog.-Philosophy

 The optimal solution to the overall problem depends upon the optimal solution to its subproblems. This simple optimization reduces time complexities from exponential to polynomial.

0/1 knapsack problem- Dynamic Prog.

$$M[i, w] = \max(M[i-1, w], M[i-1, w-w[i]] + p[i])$$

Where p[i]- is profit from i th object

$$M[i, w] = \max(M[i-1, w], M[i-1, w-w[i]] + p[i])$$

$$M[2,4] = \max(M[1,4], M[1,4-4] + p[2])$$

$$M[2,4] = \max(M[1,4], M[1,0] + 3)$$

$$M[2,4] = \max(2,0+3)$$

$$M[2,4] = 3$$

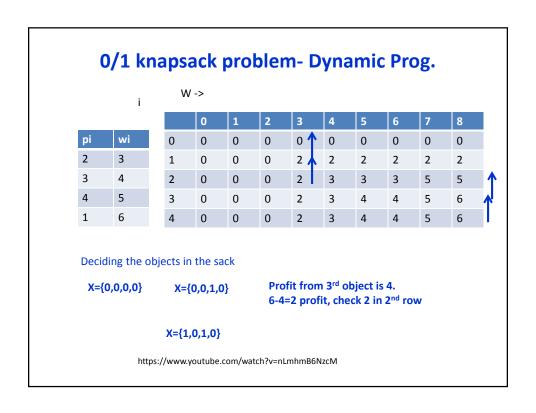
$$M[i, w] = \max(M[i-1, w], M[i-1, w-w[i]] + p[i])$$

$$M[2,7] = \max(M[1,7], M[1,7-4] + p[2])$$

$$M[2,7] = \max(M[1,7], M[1,3] + 3)$$

$$M[2,7] = \max(2,2+3)$$

$$M[2,7] = 5$$



Time complexity of Dynamic programming is O(n*w) (polynomial time), where n- number of objects and W is the knapsack capacity. Using Brute-force approach is O(2^n) (exponential time)

Solve 0/1 knapsack problem using Dynamic Prog.

Weights={2,3,4,5}, Profit={1,2,5,6}, capacity W=8 and N=4

TSP-Time complexity

For a pnroblem of size n cities, there can be 2ⁿ subsets of set S.

Each subset contains max n cities. Thus, there are 2^n n subproblems.

To solve each problem we need O(n) linear time, thus

$$T(n) = O(2^n.n.n) = O(2^n.n^2)$$