



Solving the Traveling Salesman Problem with Dynamic Programming

Session No.: 35
Course Name: Design and Analysis of Algorithms
Course Code: R1UC407B
Instructor Name: ANKIT VERMA
Duration: 50 minutes
Date of Conduction of Class:

Quick Recap of Previous Session 34

- **Instructions:**

- Let's refresh our memory with a quick Woodclap quiz on the last session's topic: Dynamic Programming and the Longest Common Subsequence Problem.
- Please take 5 minutes to answer the quiz questions.

How to participate?



1

Go to woodclap.com

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top banner

Beyond Brute Force and Greedy

We've explored brute force, greedy techniques, and divide and conquer.

Now, let's tackle a classic optimization problem with dynamic programming.

Let's brainstorm some ideas and applications using a Woodlap word cloud.

How to participate?



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Learning Outcomes:

By the end of this session, you will be able to

Learning Outcome 1:

Define the Traveling Salesman Problem and its relevance.

Learning Outcome 2:

Apply the dynamic programming algorithm to solve TSP and analyze the algorithm's time and space complexity.

Session Outline

- 1 Travelling Salesman Problem
- 2 Dynamic Programming
- 3 TSP using Dynamic Programming
- 4 Time Complexity
- 5 Space Complexity
- 6 Conclusion

What is the Traveling Salesman Problem?

Formal Definition:

"Given a list of cities and the distances between each pair of cities, what is the shortest possible route that visits each city exactly once and returns to the origin city?"

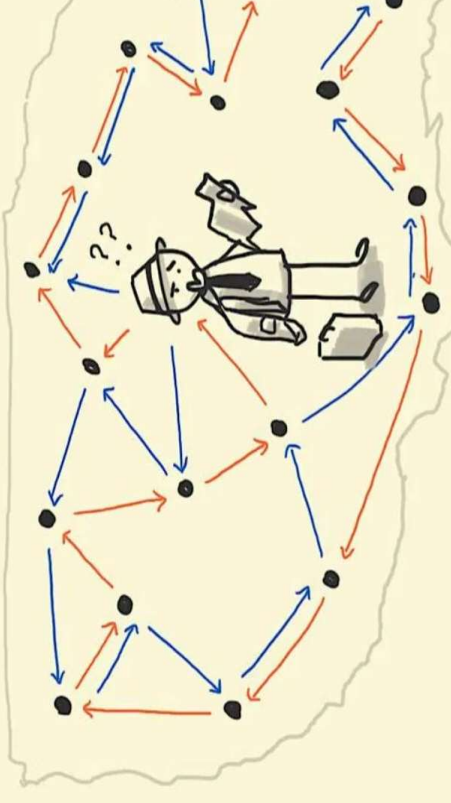
Significance:

Logistics and Transportation: Optimizing delivery routes, minimizing transportation costs.

Circuit Design: Finding the shortest path for connecting components on a circuit board.

Other Applications: Planning, manufacturing, and DNA sequencing.

THE TRAVELLING SALESMAN
WHAT'S THE SHORTEST ROUTE TO VISIT
AND RETURN?



ADDING MORE STOPS TAKES
LONGER AND LONGER AND LONGER TO FIGURE OUT

Activity 1 - Wooclap Poll : Testing Your Understanding

How to participate?



1

Go to wooclap.com

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The Need for Dynamic Programming

Limitations of Previous Approaches:

Brute-force: Exhaustively trying all possible permutations of cities quickly becomes computationally infeasible as the number of cities (n) increases.
The time complexity is $O(n!)$, making it impractical for larger problems.

Greedy Approach: While greedy algorithms can provide quick solutions, they don't guarantee an optimal solution for TSP.
Greedy choices at each step might lead to a locally optimal solution that is not globally optimal.

Divide and Conquer: Although effective for some problems, divide and conquer doesn't easily apply to the interconnectedness of the subproblems.
Dividing the TSP into smaller tours and combining them doesn't guarantee the shortest overall tour.

The Need for Dynamic Programming

Dynamic Programming as a Solution:

Dynamic programming overcomes these limitations by exploiting the problem's inherent structure.
Optimal Substructure: An optimal solution to the TSP contains within it optimal solutions to subproblems.

For example, the shortest tour that includes a specific subset of cities must also contain the shortest paths between those cities.

Overlapping Subproblems: The same subproblems are encountered multiple times when enumerating different tours.

Dynamic programming stores the solutions to these subproblems, avoiding redundant computations and significantly improving efficiency.

Activity 2 - Dynamic Programming for TSP : Building the Optimal Tour

Step-by-Step Explanation:

1. Define the DP Table:
 - We'll use a 2D table $dp[S][j]$, where:
 - S represents a subset of cities.
 - j represents the last city visited in the subset S .
 - $dp[S][j]$ stores the minimum cost to visit all cities in the subset S , starting from city 1 and ending at city j .
2. Initialize Base Cases:
 - For all $j \neq 1$, $dp[\{1\}][j] = cost[1][j]$, where $cost[i][j]$ is the distance between city i and city j .
 - This means the cost to travel from city 1 to any other city j when only those two cities are in the subset is simply the direct distance between them.

3. Fill the Table:

- We'll fill the table in increasing order of subset size.
- For each subset S of size greater than 2, ending city j in S :
 - $dp[S][j] = \min(cost[k][j] + dp[S-\{j\}][k])$ for all k in S such that $k \neq j$.
 - This means we find the minimum cost for each subset S by considering all possible previous cities k in S (excluding j itself), and adding the cost of the optimal sub-tour ending at k to the direct distance from k to j .

4. Trace Back:

- Start from the final entry in the table, $dp[all\ cities][1]$, which represents the minimum cost of the complete tour.
- To reconstruct the optimal tour, trace back from city 1 by identifying the previous city k that was used to reach city 1, and so on, until you reach city 1. This gives the sequence of cities in the optimal tour.

Activity 2 - Dynamic Programming for TSP : Building the Optimal Tour

- Illustrative Example: Cities: A, B, C, D
- Cost Matrix:

	A	B	C	D
A	0	10	15	20
B	10	0	35	25
C	15	35	0	30
D	20	25	30	0

DP Table:

S	j	dp[S][j]	Calculation
{A}	A	0	Base case
{A}	B	10	Base case (cost[A][B])
{A}	C	15	Base case (cost[A][C])
{A}	D	20	Base case (cost[A][D])
{AB}	B	20	$\min(\text{cost}[A][B] + \text{dp}\{\{A\}\})$
{AC}	C	25	$\min(\text{cost}[A][C] + \text{dp}\{\{A\}\})$
{AD}	D	30	$\min(\text{cost}[A][D] + \text{dp}\{\{A\}\})$
{ABC}	B	40	$\min(\text{cost}[C][B] + \text{dp}\{\{A\}\})$ $\text{dp}\{\{AC\}\}[A] = \min(35$
{ABC}	C	45	$\min(\text{cost}[B][C] + \text{dp}\{\{A\}\})$ $\text{dp}\{\{AB\}\}[A] = \min(35$
...
{ABCD}	A	80	(Calculated based on

Activity 2 - Dynamic Programming for TSP : Building the Optimal Tour

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{AD}	D	30	$\min(\text{cost}[A][D] + \text{dp}[\{A\}][D])$
{ABC}	B	40	$\min(\text{cost}[C][B] + \text{dp}[\{A\}][B])$ $\text{dp}[\{AC\}][A] = \min(35, 40)$
{ABC}	C	45	$\min(\text{cost}[B][C] + \text{dp}[\{A\}][C])$ $\text{dp}[\{AB\}][A] = \min(35, 45)$
...
{ABCD}	A	80	(Calculated based on previous values)

3. Trace Back:

- Starting from $\text{dp}[ABCD][A] = 80$, we find that the previous city that led to this minimum cost was city C ($\text{cost}[C][A] + \text{dp}[ABC][C] = 15 + 65 = 80$).
- From $\text{dp}[ABC][C] = 65$, the previous city was B ($\text{cost}[B][C] + \text{dp}[AB][B] = 35 + 30 = 65$).
- From $\text{dp}[AB][B] = 30$, the previous city was A ($\text{cost}[A][B] + \text{dp}[A][A] = 10 + 20 = 30$).
- Therefore, the optimal tour is $A \rightarrow D \rightarrow B \rightarrow C \rightarrow A$ with a total cost of 80.



Activity 2 - Wooflash Flashcards : Mastering the Algorithm

Instructions:

Let's create Wooflash flashcards for key terms and steps in the dynamic programming algorithm for TSP

Key terms:

Subset: A smaller set of cities chosen from the complete set.

Cost/Distance: The distance between two cities, which contributes to the total tour cost.

Memoization: Storing the results of expensive function calls and returning the cached result when the same inputs occur again.

Base Case: The simplest subproblem that can be solved directly without recursion.

Recursive Case: A more complex subproblem that is solved by breaking it down into smaller subproblems and combining their solutions.

Steps:

Define the DP Table: Create a table to store subproblems.

Initialize Base Cases: Fill in the table with the simplest subproblems.

Fill the Table: Use a recursive approach to solve subproblems based on the solutions of smaller subproblems.

Trace Back: Once the table is filled, trace back to reconstruct the optimal solution to the problem.

"Exchange your flashcards with a partner for peer learning."

Activity 2 – Reflection : Efficiency of Dynamic Programming

Comparison to Brute-Force:

- Brute-force explores all possible permutations, leading to a factorial time complexity of $O(n!)$.
- Dynamic programming drastically reduces computations by storing and reusing solutions to overlapping subproblems.
- For example, with 10 cities, brute-force would require evaluating 3,628,800 permutations, while dynamic programming reduces this significantly.

Time and Space Complexity

Time Complexity: The dynamic programming algorithm for TSP has a time complexity of $O(n^2 * 2^n)$. This is because it considers all possible subsets of cities, and for each subset, it considers all possible starting and ending cities (n) and all possible cities (n).

Space Complexity: The space complexity is $O(n * 2^n)$ due to the size of the DP table, which stores the optimal solution for each subset and ending city.

Conclusion – Summary : Key Takeaways

- The Traveling Salesman Problem is a classic optimization problem with various real-world applications.
- Dynamic programming is an efficient technique for solving TSP by breaking it into smaller subproblems.
- The dynamic programming algorithm for TSP has a time complexity of $O(n^2 * 2^n)$ and space complexity of $O(n * 2^n)$.

Information about the next lesson

- In the next session, we will explore another application of dynamic programming:
Finding the shortest path in Multistage Graphs.
- Please come prepared by reviewing the relevant sections on Multistage Graphs and dynamic programming in your textbook.