

# **B. Tech. Project**

## **Search Algorithms for E-commerce**

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### **Motivation**

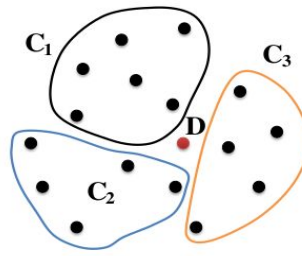
To survive in today's market E commerce companies need to cut down their delivery costs while satisfying customer's requirements. Thus finding optimal delivery routes is a major and interesting problem to solve.

### **Problem Statement**

- To identify an efficient routing between a set of storage depots to various customer locations satisfying their respective demands and time constraints.
- The goal is to minimize the total distance from all the depots respecting those constraints.

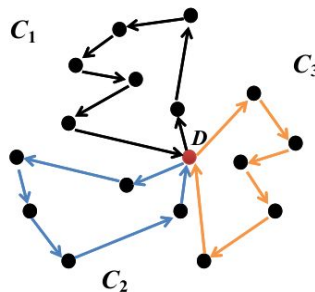
### **Algorithm: Beam Search based Approximate Algorithm**

- **Why Beam Search?**
  - In the real world scenario the set of customers can be very large.
  - Optimal Algorithms like best first search have space issues since exploring all nodes is not efficient.
  - Beam search solves the issue and finds an approximate optimal solution.
  - We also use local search algorithms on top of the solution found by beam search to further improve the solution.
- **Algorithm Phase-1: K means Clustering**
  - Divide the set of customers into disjunctive clusters using K means clustering.
  - Each cluster will be assigned one delivery vehicle respecting its capacity constraints.



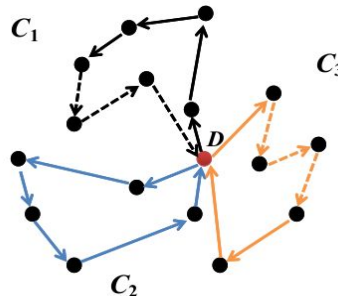
- **Algorithm Phase-2: Beam Search**

- Determine a feasible route for the vehicle in each cluster using Beam search algorithm.
- The time windows of the customers must be satisfied.



- **Algorithm Phase-3: Local Search**

- Apply local search algorithms to further improve the solutions found using beam search. (covered in detail later)



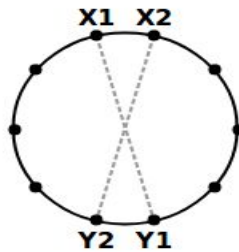
- **Error: Relaxed time windows**

- Solution not found for many cases for strict time windows.
- Introduced Error as a measure of time window violation, which depends on customer priority.
- The algorithm now finds a solution even when the time windows are not satisfied, but with some error.

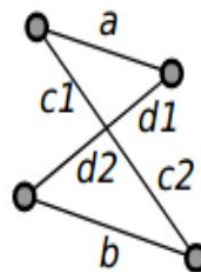
- **Extension to multiple depot locations**
  - Sorted customers based on 3 different heuristics:
    - Earliest time and Latest time and Priority
    - Distance
  - Assigned sorted customers to their nearest depot making sure that the total customer demand does not exceed the depot total capacity.

## Local Search Analysis

- **2-OPT algorithm**
  - Given any route and 2 different pairs of consecutive nodes in the route, it can be shortened by exchanging 2 links (hence 2-OPT)
  - If the condition,  $d(X1, Y1) + d(X2, Y2) < d(X1, X2) + d(Y1, Y2)$  holds and the time windows are satisfied, then we remove links  $X1-X2$  and  $Y1-Y2$  and replace with  $X1-Y1$  and  $X2-Y2$ .

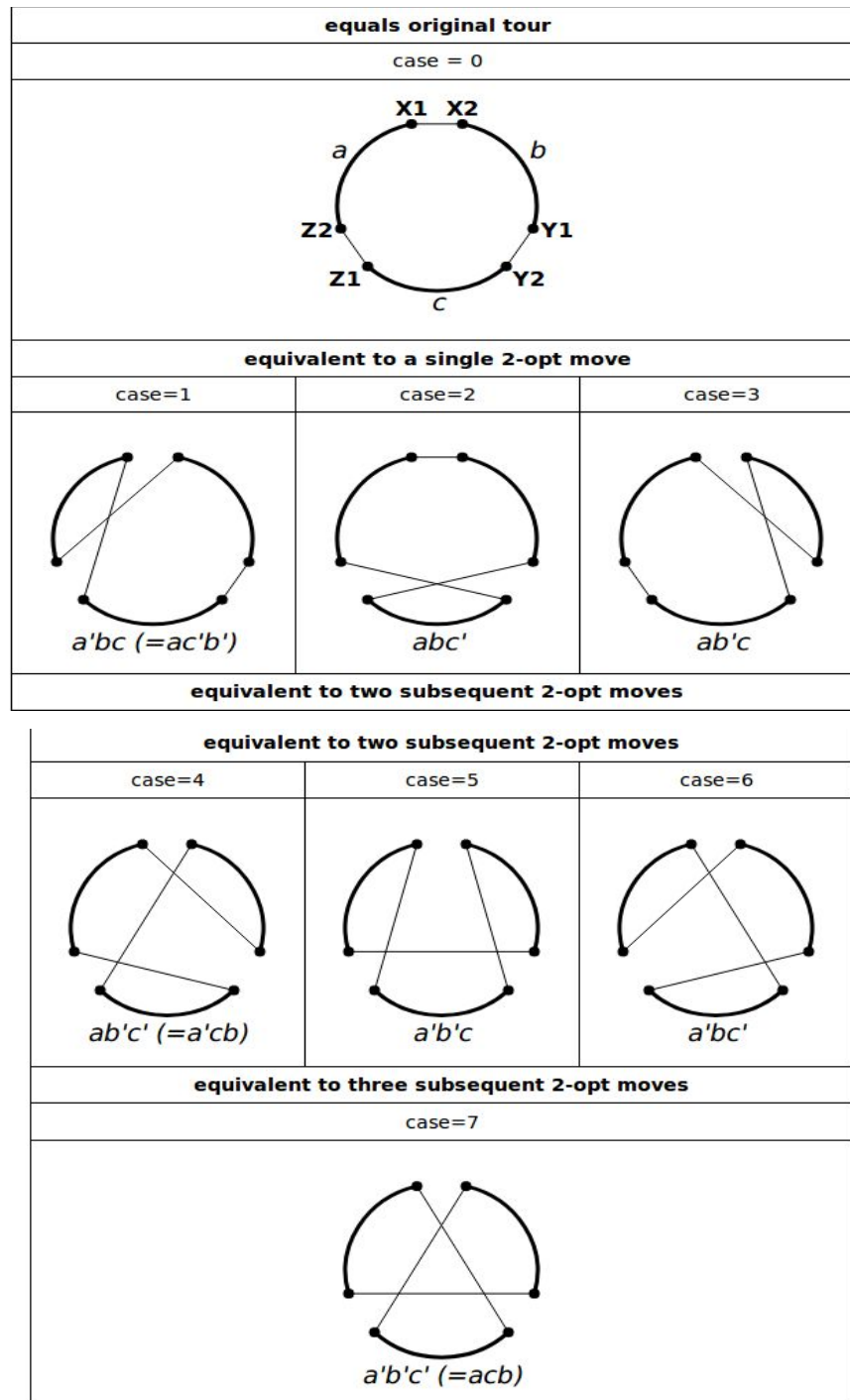


- **Observation**
    - Since our distance metric is Euclidean, the tour without intersections would be shorter than the tour with intersections
- $$a < c1 + d1$$
- $$b < c2 + d2$$
- $$a + b < (c1 + c2) + (d1 + d2)$$



- **Multiple Swaps: 3-OPT**

- In 2-OPT move we remove 2 links from cyclic tour, thus obtaining 2 open segments, which we manipulate and combine them to get a new tour.
- In 3-OPT we remove 3 links, obtaining 3 segments to manipulate.
- This gives us 8 combinations including the tour identical with the initial one.



- **Why 3-OPT?**

- Each 3-OPT move is either identical with 2-OPT move or is equal to a sequence of two or three 2-OPT moves
- It is possible that there exists a sequence of 2-OPT moves that improves the tour but it begins with 2-OPT move that increases the length of the tour.
- This sequence is not achieved when we use 2-OPT only because of that initial “bad” move.

- **Efficiency Issue**

- Any K-OPT(performing K swaps) is better than (K-1)-OPT(performing K-1 swaps)
- But Complexity for K-OPT for finding one single improvement is  $O(n^k)$ .
- So, can we improve the efficiency of K-OPT?

- **First Improvement**

- If for a given customer  $X_1$ , we previously did not find any improving move and it still has the same neighbours, then chances that we will find an improvement now is small.
- We use special flag for each of the customers called don't look bits. Initially all the flags are turned off, which means we allow searching.
- If the search for improvement from customer  $X$  fails then the bit for that customer is turned on. If a move is performed which involves customer  $X$ , then the flag is turned off.
- Now, when we are searching for candidates for customer  $Y$ , we skip all customers with their flag turned on.

- **Second Improvement**

- Suppose that for some  $X_1, X_2, Y_1, Y_2$ :

$$d(X_2, Y_2) \geq d(X_1, X_2)$$

$$d(X_1, Y_1) \geq d(Y_1, Y_2)$$

- But, for 2-OPT to hold,

$$d(X_1, Y_1) + d(X_2, Y_2) < d(X_1, X_2) + d(Y_1, Y_2)$$

- Therefore, one of the below 2 conditions must hold,

$$d(X_2, Y_2) < d(X_1, X_2)$$

$$d(X1, Y1) < d(Y1, Y2)$$

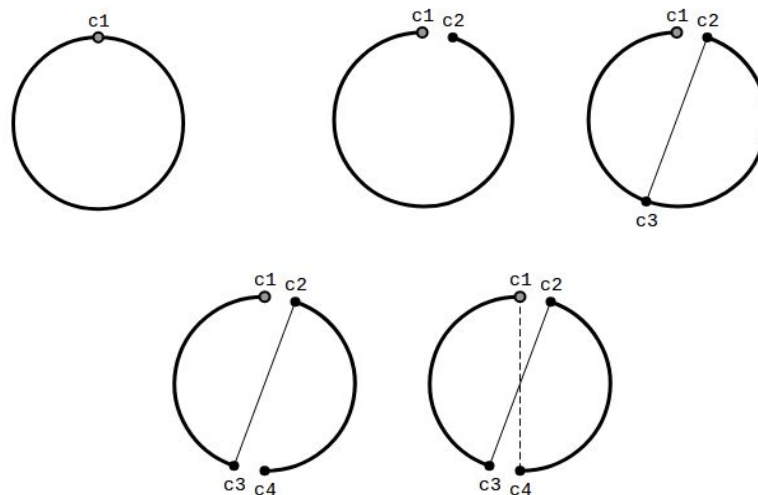
- Let us analyze the first condition

$$d(X2, Y2) < d(X1, X2)$$

- So In 2-OPT, for a given vertex  $X1$ , considering it's neighbour  $X2$ , we can search around  $X2$  for vertices  $Y2$  which are closer than  $d(X1, X2)$  (Basically in a fixed radius neighbourhood) and accept the first improving 2-exchange move.

### • Sequential Moves

- Consider a sequence of 2-OPT moves
- Start from certain customer  $C1$  on tour.
- Remove link between  $C1$  and one of its tour neighbours,  $C2$
- Add link between  $C2$  and some other customer  $C3$
- Remove link between  $C3$  and its neighbor  $C4$ .
- Add link between  $C4$  and the first customer  $C1$ , to close the tour.



- Note that steps 1 and 2 have the same scheme: remove a link between a city and it's route neighbor and then add link between this neighbor and some other city. Each step exchanges two links.
- This can be done similarly for 3-opt as well.
- Basically this is to show that every k-opt swap can be expressed as a sequence of moves where each move is equivalent to removing a link between a city and its tour neighbour and then add a link between this neighbour and some other city.

- So in K-OPT should I consider all possible K sequential moves(there are totally  $O(n^k)$  moves) or is there a better solution?

- **Improving move condition**

- A move is improving when it is valid and it improves a tour. Any k-opt move that improves a tour must fulfill the condition: Sum of lengths of links removed from tour must be greater than sum of links added to route.
- In other words sum of links removed from tour must be greater than sum of links added to route.
- Let us take a sequential move of a K-swap solution. Define

$$g_1 = \text{distance}(c_1, c_2) - \text{distance}(c_2, c_3) \text{ \# gain from step 1}$$

$$g_2 = \text{distance}(c_3, c_4) - \text{distance}(c_4, c_5) \text{ \# gain from step 2}$$

$$g_3 = \text{distance}(c_5, c_6) - \text{distance}(c_6, c_7) \text{ \# gain from step 3}$$

$$\text{and so on .. } G_k = \sum_{i=1}^k g_i$$

- For solution to be improving  $G_k > 0$
- Although some of  $g_1, g_2, g_3...$  may be negative, when this *sum* of numbers is positive then the move is an improving move

- **Observations**

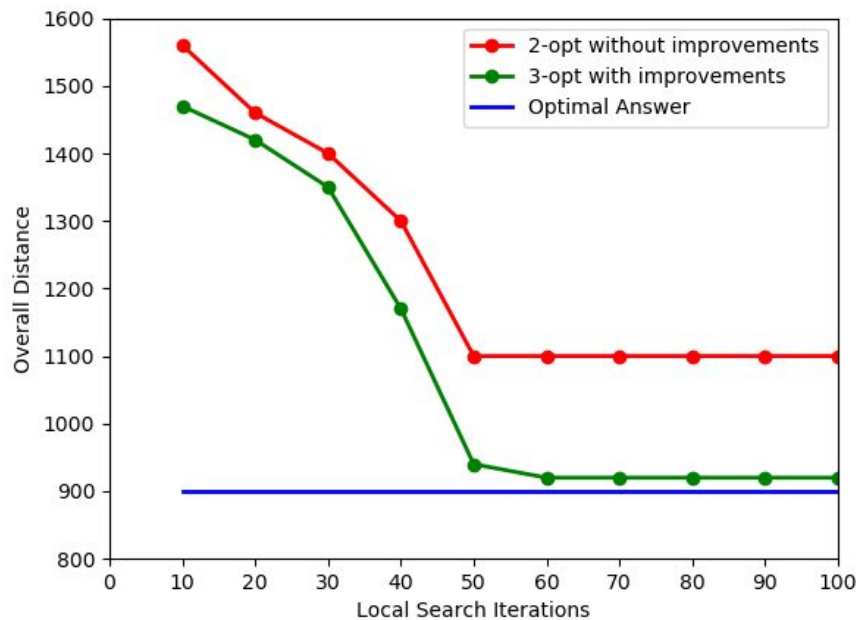
- We should note that sequential moves are *cyclic*, we can start from any step of move and apply them one by one, until we make them all.
- So is there a specific order in which we can process these sequential moves instead of checking all possible orders for a given set of sequential moves?
- Theorem: If a sequence of numbers has a positive sum, there is a cyclic permutation of these numbers such that *every partial sum* is positive.
- In particular, then, since we are looking for sequences of gains  $g_i$ 's that have positive sum, *we need only consider sequences of gains whose partial sum is always positive*. This gain criterion enables us to reduce enormously the number of sequences we need to examine!
- Thus we found a huge reduction in the number of moves we have to check for a K-opt solution

- Therefore during process of building a sequential move we check partial sum of gains. If this sum remains positive before the last, closing step, then a sequence of exchanges is *promising* and we can continue, even if it is not valid move now.

## **Results**

- **Local Search Improvement vs the number of iterations**

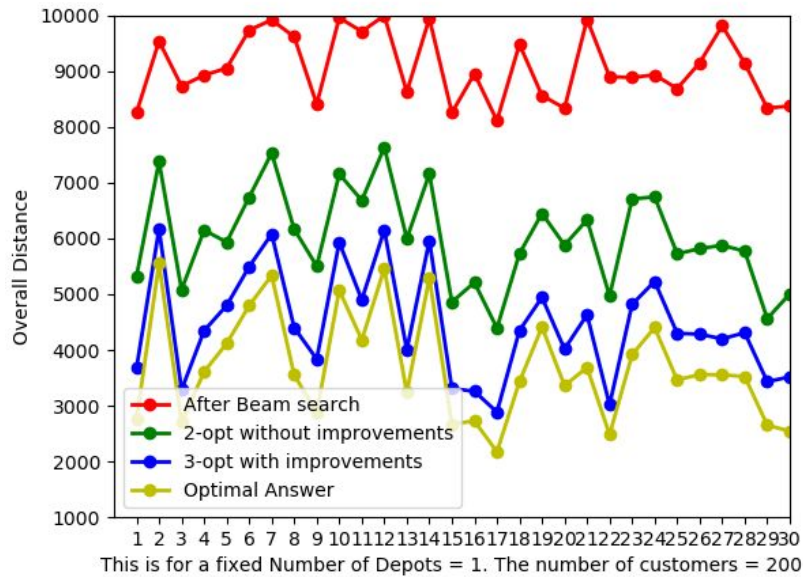
- This is for one depot and 200 customers
- As the iterations increase the local search solution improves but after a point it gets stuck at local minimum
- It's clear that 3-OPT is better than 2-OPT.



- **Local Search Improvement on various test cases**

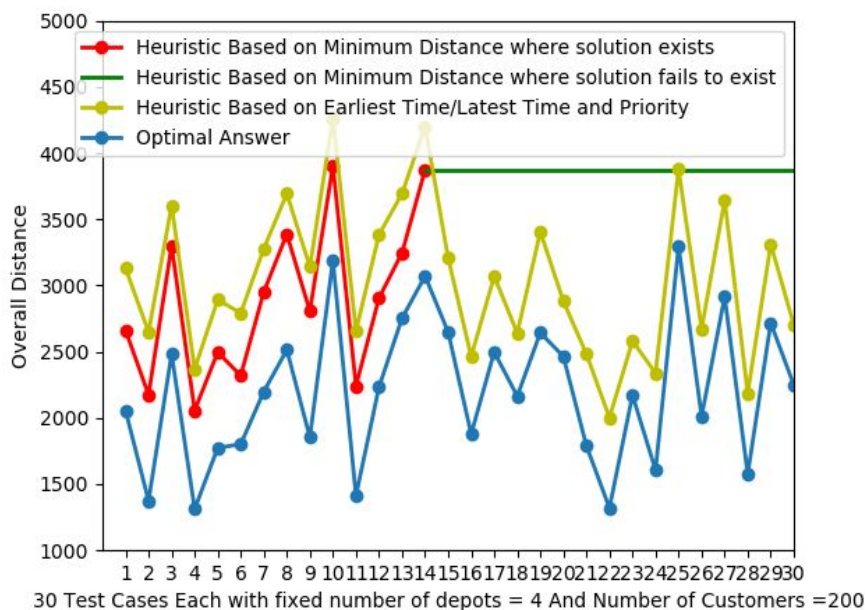
- The gap between beam search solution and 2-OPT solution is much more than the gap between the 3-OPT and 2-OPT solution





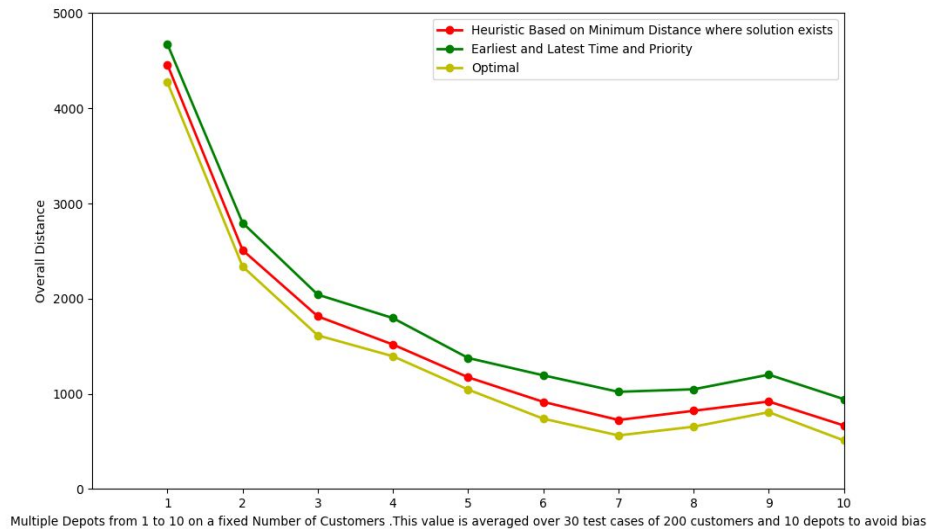
- **Heuristics Performance Comparison on various test cases**

- In the heuristic criteria of minimum distance we just assigned based on minimum distance.
- Even though it performs better than other heuristics, it fails to find a solution on certain cases highlighted by green



- **Heuristics Performance Comparison**

- On an average the distance reduces by a factor of the number of depots



- **Local Search Time Performance Comparison**

- Since 3-opt is  $O(n^3)$  the general observation is that as number of customers double the time factor increase proportionately.
- Also notice that the cyclicity observation decreased the time by a larger amount since for every cyclic permutation we reduced by a factor of 3 if there existed a solution
- Other improvements were minor and did not much effect on the time

