### VRP Literature Review 1

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### Introduction to VRP Problem (From the most basic)

In the Vehicle Routing Problem (VRP), the goal is to find optimal routes for multiple vehicles visiting a set of locations (When there's only one vehicle, it reduces to the Traveling Salesperson Problem.)

But what do we mean by "optimal routes" for a VRP? One answer is the routes with the least total distance. However, if there are no other constraints, the optimal solution is to assign just one vehicle to visit all locations, and find the shortest route for that vehicle. This is essentially the same problem as the TSP.

A better way to define optimal routes is to minimize the length of the longest single route among all vehicles. This is the right definition if the goal is to complete all deliveries as soon as possible. The VRP example below finds optimal routes defined this way.

### How is our problem different from original VRP ?

For taxi-booking apps, there are multiple evaluation standards for a successful dispatching strategy. For instance, we can maximize the acceptance rate between drivers and riders, or we can maximize the total benefits produced by the dispatching strategy

This paper proposes a dispatch system to maximize global success rate of bookings using **Combinatorial Optimization**. Also it proposes a method to predict destinations of a user once he/she starts the APP.

#### Introduction

**Traditional Dispatching System**: Find the nearest driver or a shortest-travel-time driver for each individual order without judging whether these drivers were more suitable for other orders. Finding local minimum does not necessarily means getting global minimum.

NTU Cab: In order to minimize the waiting-time or the pick-up distance globally, this model considers each agent as a computation unit. Each computation unit processes N order/driver pairs and each order is dispatched to only one driver. An order will be dispatched to another driver if the matched driver does not accept it. The methods do not optimize the total success rate.

#### How to use combinatorial optimization model?

Three elements in the dispatching system: departure time, origin and destination of the order.

#### Order Dispatch System:

As the matrix shows, the sum of each column is less than 1.

$$\begin{pmatrix} a_{11} & \cdots & a_{1M} \\ \vdots & a_{ij} & \vdots \\ a_{N1} & \cdots & a_{NM} \end{pmatrix}, \text{ where } 1 \le i \le N, 1 \le j \le M,$$

and 
$$a_{ij} = \begin{cases} 1 & \text{order } i \text{ is dispatched to driver } j, \\ 0 & \text{order } i \text{ is not dispatched to driver } j. \end{cases}$$

In this scenario, a driver receives only one order at each round, while one order can be dispatched to several drivers. This imposes the following constraint:  $\forall j, \sum_{i=1}^{N} a_{ij} \leq 1$ .

Figure 1: Dispatch Matrix

#### Probability of acceptance

In Didi Chuxing's business scenario, an order is dispatched to a number of drivers, and each driver decides whether or not to accept it according to his or her own preference. For each order, whether it is accepted by one of the drivers is directly related to each driver's probability of acceptance.

#### Two submodels

One model predicts each driver's action, in which estimating the probability of a driver accepting an order.

Another model formulates an optimization problem for maximizing the target  $E_{SR}$  using the estimated acceptance probabilities.

#### Submodel 1

Use binary variable  $\boldsymbol{y}$  for outcome, where 1 is acceptance and 0 is rejection

 $p_{ij}$  is the probability of order i being accepted by driver j

 $x_{ij}$  is the predictor vector to determine  $p_{ij}$ , including distance, direction and other variables...

Then the paper uses previous  $< O_i, d_j >$  pairs as training data with Logistic Regression and GBDT.

Now we already get the probability. Let's come to optimization

The probability  $O_i$  is accepted:

$$E_i = 1 - \prod_{j=1}^{M} (1 - p_{ij})^{a_{ij}},$$

where  $p_{ij}$  is defined in Eq. (1)

and 
$$a_{ij} = \begin{cases} 1 & \text{order } i \text{ is dispatched to driver } j, \\ 0 & \text{order } i \text{ is not dispatched to driver } j. \end{cases}$$

The success rate is:

$$\begin{cases} \max_{a_{ij}} E_{SR} = \frac{\sum_{i=1}^{N} [1 - \prod_{j=1}^{M} (1 - p_{ij})^{a_{ij}}]}{N}, \\ \text{s.t. } \forall j, \sum_{i=1}^{N} a_{ij} \leq 1, a_{ij} \in \{0, 1\}. \end{cases}$$

The paper firstly uses hill-climbing method to solve the optimization problem, which is an NP hard problem.

Then the paper adds a destination prediction model

#### Submodel 2

Some Interesting Patterns:

- Same users tend to go to same destinations at similar times
- Users go to a fixed set of locations for shopping in weekends
- order's location provides useful information for destination prediction. Other information such as the driver information, traffic situation, driving speed, etc. have weak correlations with the destination

Then submodel 2 uses Bayesian Classifier to predict  $Y=y_i$  based on X=(T,Lng,Lat)

#### Conclusion

This paper proposes a novel order dispatch model which has been deployed in the online system at Didi Chuxing. It aims to maximize the global success rate and thus optimizes the overall acceptance rate and delivers the best user experience. We formulate the order dispatch model as a combinatorial optimization problem, in which a key ingredient is to estimate the probability of a driver accepting an order.

#### Questions

- We also need to consider charging station?
- Is the metric "Acceptance Rate" appropriate?
- This paper deploys a traditional optimization method, how can RL be more powerful?

Thanks for Watching