An Online Approach to Solve the Dynamic Vehicle Routing Problem with Stochastic Trip Requests for Paratransit Services

Michael Wilbur[1], Salah Uddin Kadir[2], Youngseo Kim[3], Geoffrey Pettet[1], Ayan Mukhopadhyay[1], Philip Pugliese[4], Samitha Samaranayake[3], Aron Laszka[2], and Abhishek Dubey[1]

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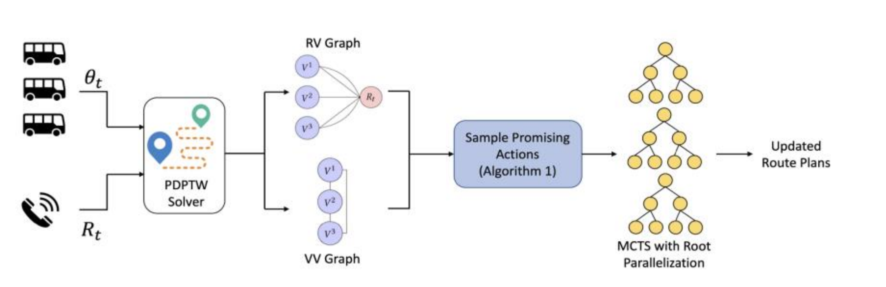
Term Paper presentation by –
Group - 19

Overview

Problem Domain

- Dynamic Paratransit

Problem Setting



- Dynamic VEHICLE ROUTING problem with scholastic trip requests

Solution Approach

- A Fully Online
- Non-myopic approach

Static vs Dynamic VRP

Static VRP

- Knows customers beforehand
- Vehicles are assigned routes for each day beforehand.

Dynamic VRP

- New Customers may arrive
- Vehicle routes needs to be updated to take in new customers

Dynamic Paratransit and Micro-transit needs to be modelled as DVRP

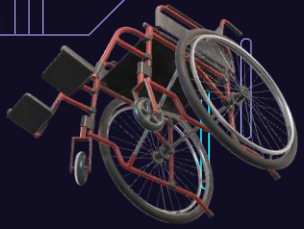
Background & Motivation...

Existing Solutions aims at:-

- Optimizing a non-myopic utility function.
- Batching requests together and optimizing a myopic utility function.

Motivation:-

- While the former approach is typically offline, the latter can be performed online.
- We point out two major issues with such approaches when applied to paratransit services in practice.
- First, it is difficult to batch paratransit requests together as they are temporally sparse. S
- econd, the environment in which transit agencies operate changes dynamically (e.g., traffic conditions can change over time), causing the estimates that are learned offline to become stale.



MAIN IDEAS OF A PITCH DECK

States

- Vehicles *v* V

INVESTORS

When it comes to picking investors for a pitch deck, it's important to research potential investors and understand their preferences, goals and interests

VALUE

The value of a product is determined by how much customers are willing to pay for it. It's a combination of factors, including the quality of the product, its features, and how well it meets customer needs

Handling Exponential Action Space

Components

- **RV-graph**: there is an edge between a request and a vehicle for every feasible route plan in which a vehicle can service the new request.
- **VV-graph**: edges represent swaps with highest utility.
- **Feasible actions**: any independent set of edges from RV U WV that includes only one edge from RV.

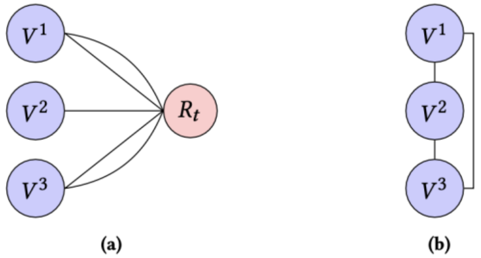


Figure 2: (a) RV-graph (G_{RV}): there is an edge between a request and a vehicle for every feasible route plan in which a vehicle can service the new request. (b) VV-graph (G_{VV}): an edge between vehicle v^i and v^j represents the swap with the highest utility between the two vehicles.

Handling Exponential Action Space

Components

The number of possible actions for a given state is combinatorially large; on average, an arbitrary state in our MDP has 10^22 possible actions. Such an action space is infeasible to explore in an online setting.

To address this challenge, we introduce an approach that enables us to sample promising actions from the set of feasible actions. We start by introducing two heuristic metrics that can be used to gauge the long-term utility of a route plan quickly.

▶ Handling Exponential Action Space

Heuristics Metrics

1.) **Maximizing the budget to serve future requests:** maximize time in which a vehicle has no passengers on board so that they are free to accommodate new requests in the future.

$$\bar{b}(\theta_t^i) = t_{max} - t - \sum_{j\in\{1,\dots,|\theta_t^i|-1\}} \mathbb{1}(w(\theta_t^i, l^j) > 0)\{a(\theta_t^i, l^{j+1}) - a(\theta_t^i, l_j)\}$$

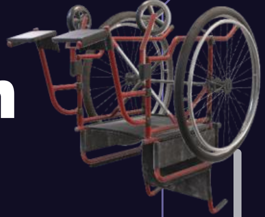
Handling Exponential Action Space

Heuristics Metrics

2.) **Minimizing passenger travel time:** maximize space available in vehicles to accommodate new requests.

$$\overline{PTT}(\theta_t^i) = \sum_{j \in \{1,\ldots,|\theta_t^i|-1\}} w(\theta_t^i, l_j) * (a(\theta_t^i, l_{j+1}) - a(\theta_t^i, l_j))$$

Monte Carlo Tree Search(MCTS) Evaluation



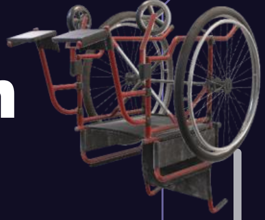
Why

Non-myopic approaches to DVRP rely on hybrid offline-online solutions in which an offline component is trained on historical data and embedded in an online search.

Offline components typically require long training periods and must be re-trained each time the environment changes, making them unsuitable for highly dynamic environments.

This motivates us to use **MCTS**, an **online probabilistic search algorithm**, to evaluate the **long-term utility of potential actions**.

Monte Carlo Tree Search(MCTS) Evaluation



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Experimental Setup

Setup as used in paper.....

- 129 days of paratransit trip requests from CARTA.
- Vary number of vehicles.
- Requests arrive 60 minutes before requested pickup time.
- Pickup and drop-off time window is 15 minutes before to 15 minutes after requested time.
- Requested drop-off time = requested pickup time + direct travel time between pickup and drop-off.