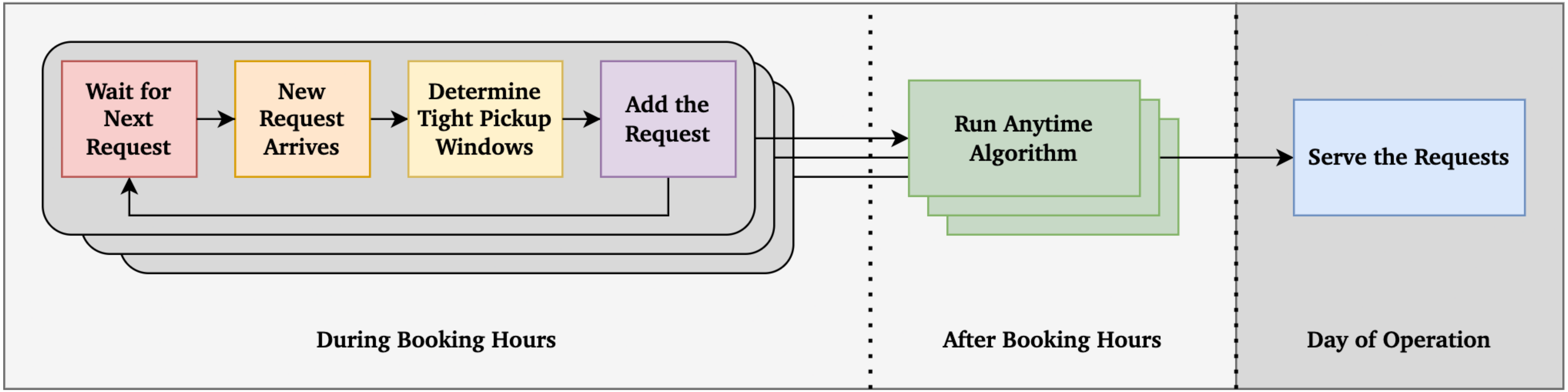
Offline Vehicle Routing Problem with Online Bookings: A Novel Problem Formulation with Applications to Paratransit

Amutheezan Sivagnanam[1], Salah Uddin Kadir[1], Ayan Mukhopadhyay[2], Philip Pugliese[3], Abhishek Dubey[2], Samitha Samaranayake[4], Aron Laszka[5]

[1]University of Houston, [2]Vanderbilt University, [3]Chattanooga Area Regional Transport Agency, [4]Cornell University, [5]Pennsylvania State University



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Vehicle Routing Problem (VRP)

Offline VRP	Online VRP
All the requests are known	Request arrives in real time
Allow large running time	Make quicker decision

We focus on the problem of online day ahead booking, where the passenger ***provides flexible broad window*** *that need to be tightened in real-time.*

Applications*: paratransit day-ahead booking, grocery delivery, etc.*

Problem Statement

How to select tight pickup windows at the time of booking, based on both requests booked so far as well as expectation of future requests?

GOAL: Learning optimal policy that determines tight pickup window during online decision making, that minimizes total travel time and number of vehicle routes required

DATA: Trip data that contains details of pickup and dropoff locations, and broad pickup windows

We partnered with **Chattanooga Area Regional Transportation Authority** (**CARTA**) and obtained the real-world paratransit trip data

Model

Online Booking Problem

Inputs:

Existing trips $(\langle \mathrm{T}_1, \ldots, \mathrm{T}_{i-1} \rangle, \langle \mathrm{w}_1, \ldots, \mathrm{w}_{i-1} \rangle)$

Current vehicle routes $(\mathrm{R}^{(i-1)})$

Incoming request (T_i, W_i)

Outputs:

Tight pickup window (w_i)

Updated vehicle routes $(\hat{\mathrm{R}}^{(i)})$

Constraints:

- Tight pickup windows should be within the broad pickup windows

$$W_i^{\text{start}} \leq w_i^{\text{start}} \leq w_i^{\text{end}} \leq W_i^{\text{end}}$$

Offline Vehicle Routing Problem

Inputs:

Trips $(\langle \mathrm{T}_1, \ldots, \mathrm{T}_i \rangle, \langle \mathrm{w}_1, \ldots, \mathrm{w}_i \rangle)$

Candidate vehicle routes $(\hat{\mathrm{R}}^{(i)})$

Outputs:

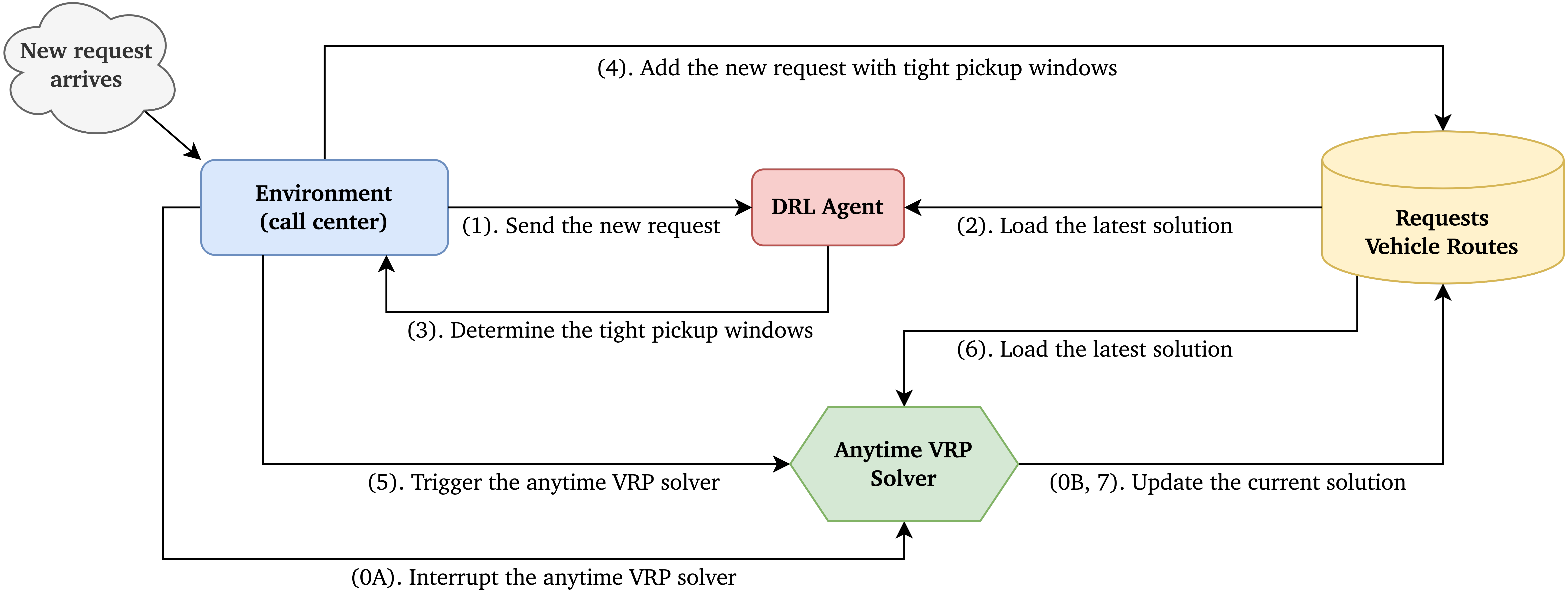
Optimized vehicle routes $(\mathrm{R}^{(i)})$

Constraints:

- Must serve all the trip requests
- Pickup and dropoff must ensure time window and capacity constraints
- Duration of vehicle route must be less than D^{maxroute}

Objective: *Select tight windows such that the optimal cost of resulting offline VRP is minimized*

Solution



New request arrives
Environment (call center)
DRL Agent
Requests Vehicle Routes
Anytime VRP Solver
(4). Add the new request with tight pickup windows
(1). Send the new request
(2). Load the latest solution
(3). Determine the tight pickup windows
(6). Load the latest solution
(5). Trigger the anytime VRP solver
(0B, 7). Update the current solution
(0A). Interrupt the anytime VRP solver

Solution

Online Booking Problem

- **State-Action**: State space is *enormous* and *complex,* to overcome the complexity we map the *state-action* into following feature vectors
  - Busyness of the area at given time of the day
  - Additional travel time/distance
  - Tightness of requests within the vehicle route
  - Expectation of future requests ($|\mathrm{T}| - i$)
- **Reward Shaping:** Rewards from environment are delayed (e.g., by 140 to 200 steps), instead we compute reward as the difference of cost (i.e., total travel time and vehicle routes required) between before and after tightening pickup windows $\tilde{c}_i = VRP^*(\mathrm{T}, \langle w_1, \dots, w_{i-1}, w_i, W_{i+1}, \dots, W_{|\mathrm{T}|}\rangle) - VRP^*(\mathrm{T}, \langle w_1, \dots, w_{i-1}, W_i, W_{i+1}, \dots, W_{|\mathrm{T}|}\rangle)$

Results

Dataset and Experimentation Setup

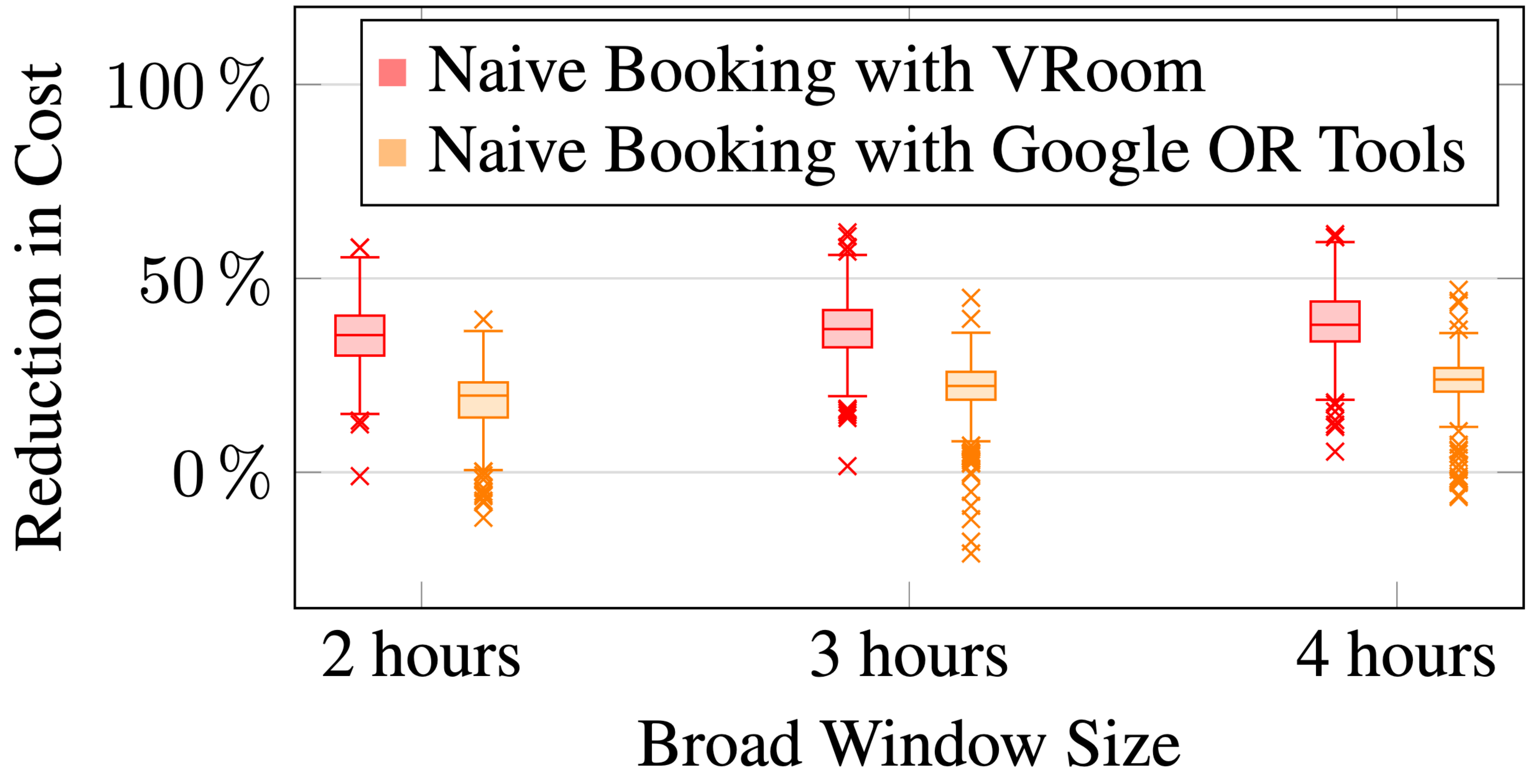
- Collect historical paratransit trip data from **Chattanooga, Tennessee**.
    - **6** months of data, with an average of **140** trips per day
- Obtain the travel time and travel distance data using **OSMNx** and **NetworkX**
- Vehicle capacity: **9**, Maximum route duration (D^{maxroute}): **10** hours
- Tight windows: **30** minutes, Broad windows: **3** hours
- Implement the entire framework in **Python 3.8** (used **TensorFlow** for Neural Networks)
- Run the experiments in **Intel Xeon E5-2680 28-core CPU** and **128 GB of RAM**

The data and code are available at https://smarttransit.ai/

NetworkX
Network Analysis in Python

Results

Numerical Results



- **Training Duration**: 1-2 Days per episode
- **Decision time**: 0.25 seconds to 2 seconds

The trained DRL agent is able to **reduce the cost** by selecting tight pickup windows during online booking compared to **naive selection** (i.e., always choose the middle of broad windows)

Conclusion

- The novel problem formulation for **online booking** by **minimizing the total travel time** and **total vehicle routes**
- **Significant reduction** in costs due to selecting tight pickup time windows using trained DRL agent instead of a naive selection
- The trained DRL agent determines the tight pickup windows within a fraction of seconds
- The DRL agent trained running the anytime algorithm between requests performs better than the DRL agent trained without running the anytime algorithm between requests

Thank You For The Attention !

For Questions
Please visit our poster at
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Amutheezan Sivagnanam
Homepage: https://amutheezan.com/

Aron Laszka
Homepage: https://aronlaszka.com/

Project URL: https://smarttransit.ai/

smarttransit.ai

University of Houston
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