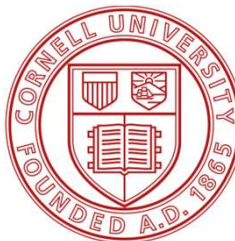
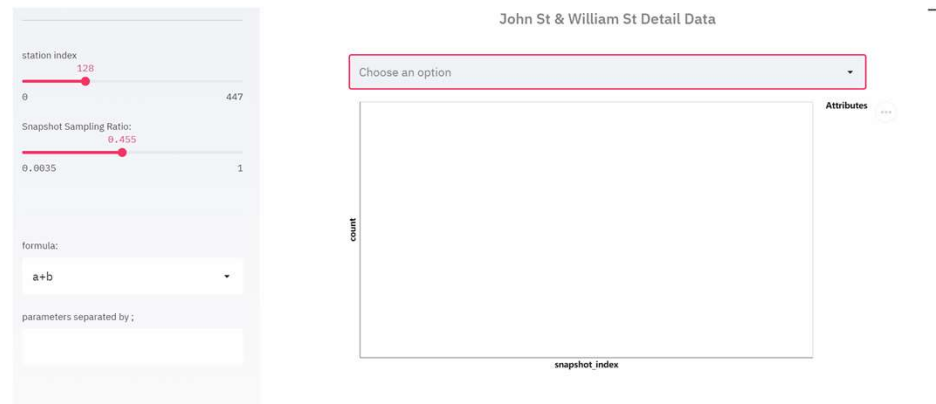


Citi Bike Management in MARO with Deep RL

Sean Sinclair,
Cornell University



MARO



Multi-Agent Resource Optimization (MARO) developed by Microsoft Asia

Simulators

Data-driven trace replays for:

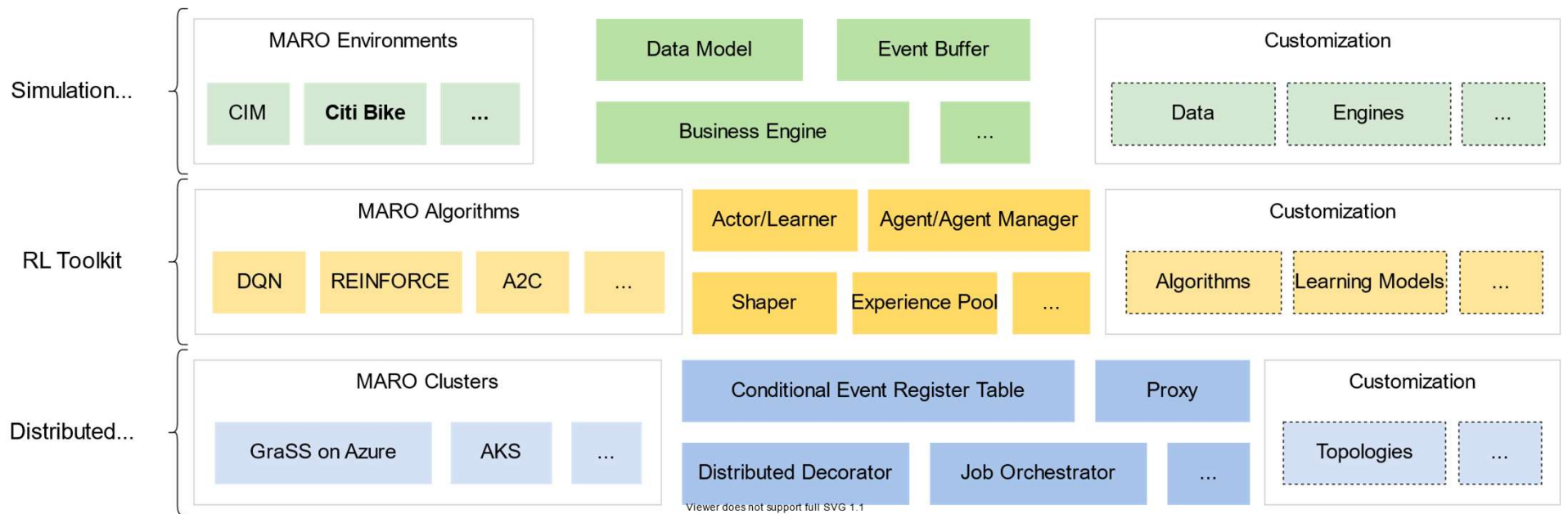
- Container inventory management
- Bike repositioning in transportation
- VM provisioning in data centers

Package Features

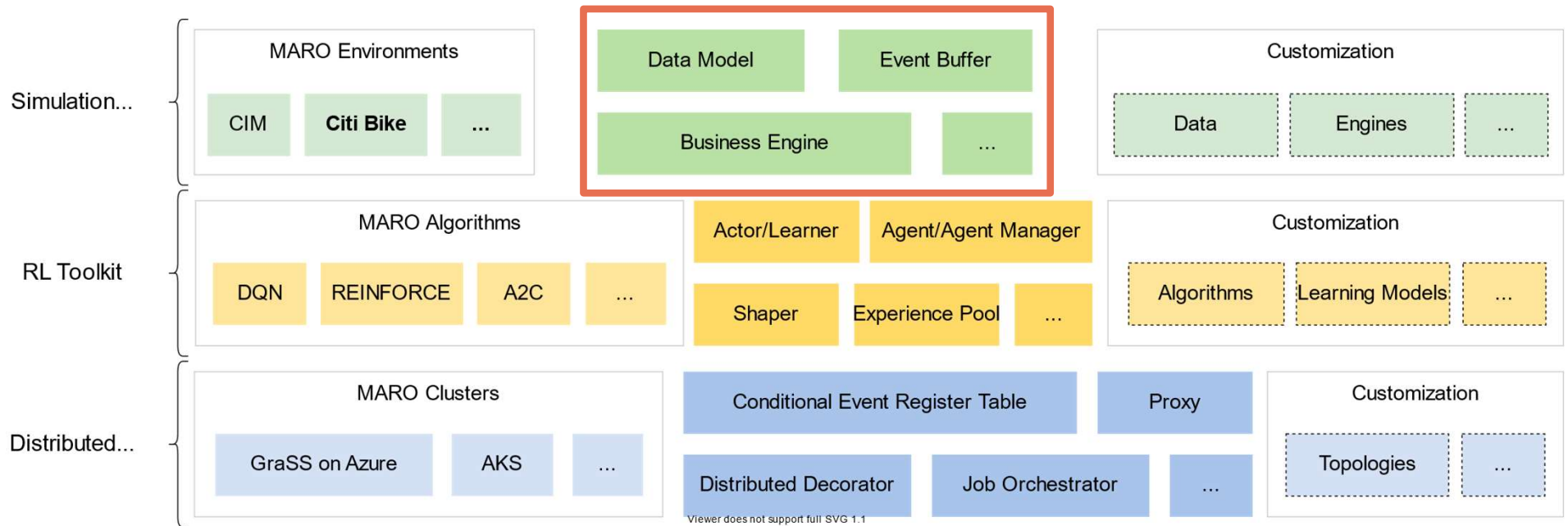
Open-source package containing:

- Simulation toolkit (not in OpenAI Gym API)
- Business engine with real-world and toy / stochastic data traces
- RL Toolkit (training, developing new algorithms)

MARO



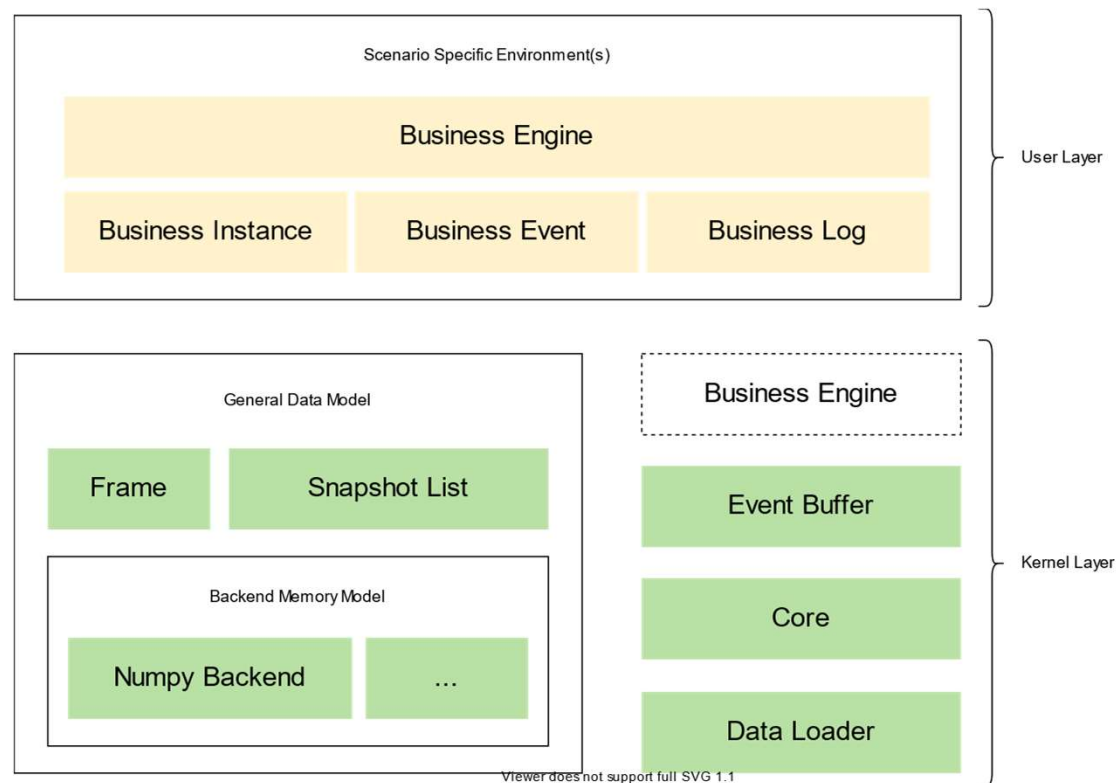
MARO



Business Engine

The MARO simulation toolkit is:

- Event driven, more friendly to business logged data
- High execution performance for real-world data (uses Cython under the hood)



Business Engine

Tick / Frame

Notion of time index:

- Most “real-world” problems do not execute in discrete time-steps
- Potential for multiple “events” per tick

Decision Event

“Issue” that needs to be addressed:

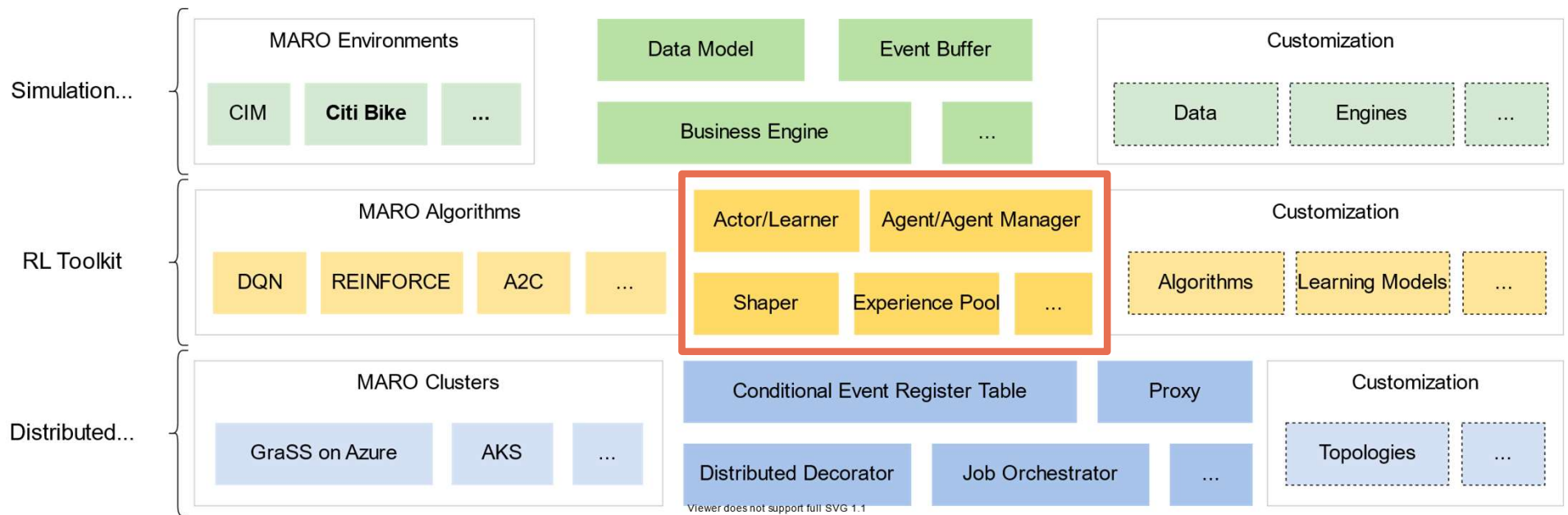
- Current VM Arrival
- Empty / full bike station
- New shipping management request
(exogenous to state of system)

Snapshot List / Frame

State information on current system:

- Physical machines and available capacity
- Set of bike stations and current number of bikes
- List of shipping routes currently in progress

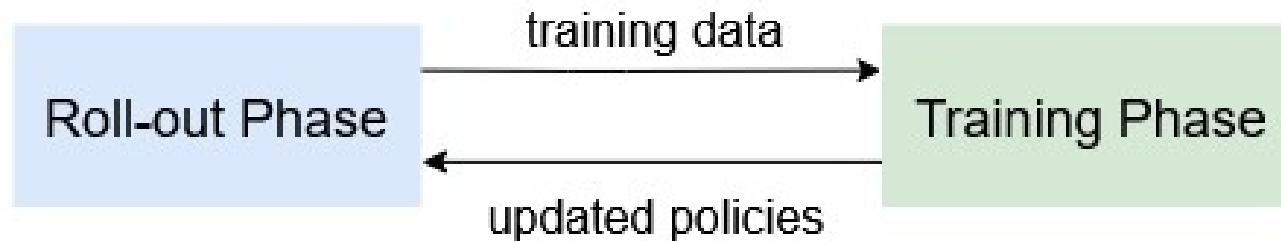
MARO



RL Toolkit

The RL toolkit contains:

- Linear, parallel, and distributed workflows for efficient algorithm training
- Code framework for algorithm development, training, neural network features
- Arbitrary “shaper” to take *business data* and transform into (*state, action reward*) information to feed into RL algorithms



Agents

The Agent specification:

- Linear, parallel, and distributed workflows for efficient algorithm training
- Code framework for algorithm development, training, neural network features
- Arbitrary “shaper” to take *business data* and transform into (*state, action reward*) information to feed into RL algorithms

Only requirement, specify action selection:

```
def choose_action(self, decision_event: DecisionEvent)
```

Takes as input decision event from the business engine, outputs a feasible “Action” object

Environment Sampler

Provides interface for RL algorithms + business engine

- How observations (snapshots) of environment are encoded into state vectors as input into the policy models (“state shaping”)
- How model outputs are converted to action objects defined by the business engine
- How rewards / penalties are evaluated (“reward shaping”)

Domain knowledge, deal with non-Markovian
structure of real-world problems

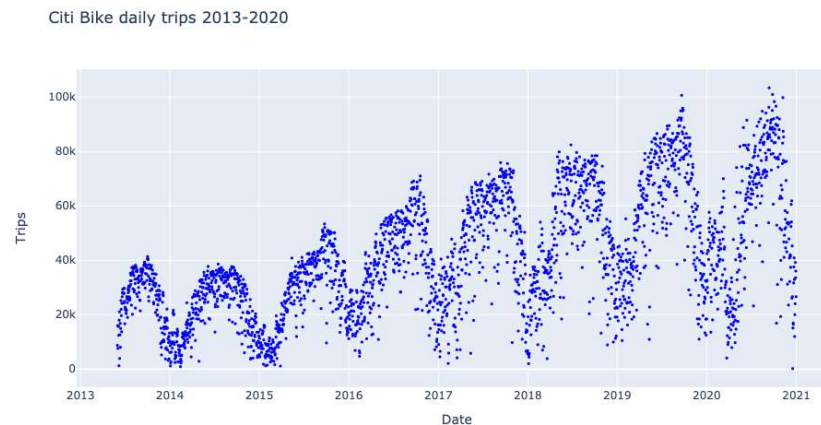
Bike Management

Simulates bike repositioning problem triggered by bike trips from CitiBike.

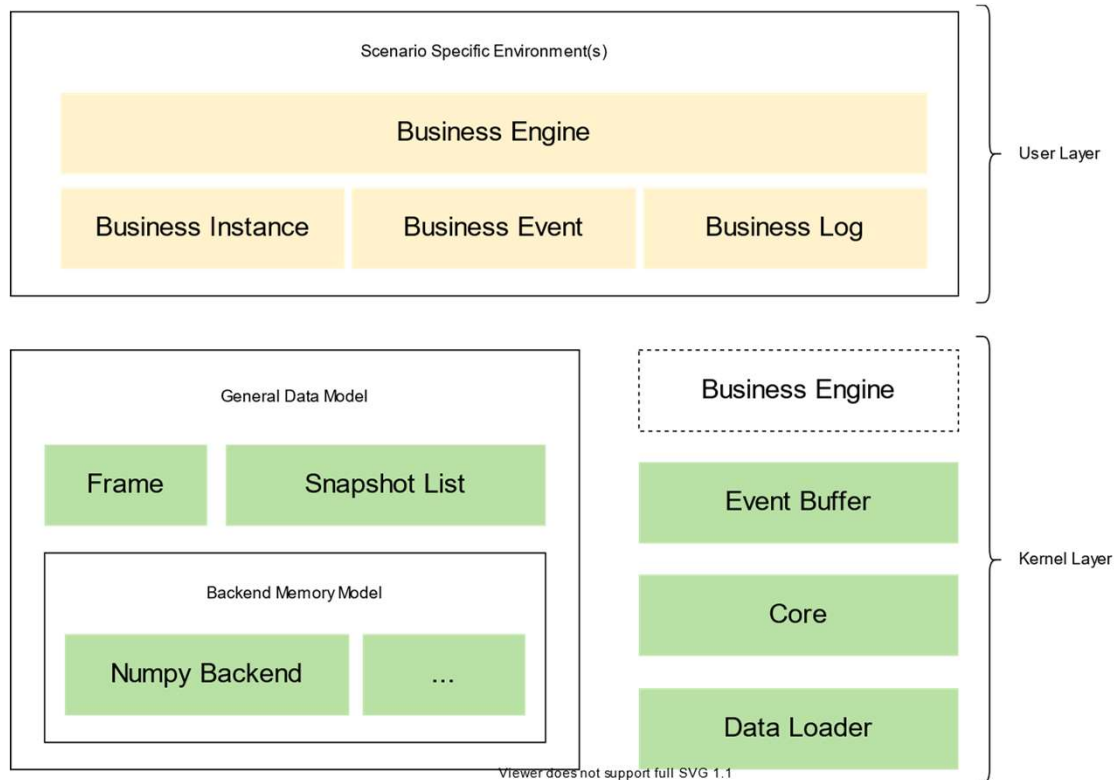
CitiBike:

- New York City's bike sharing system
- Fleet of bikes locked in a network of docking stations throughout city
- Bikes can be unlocked and returned to any other station in system

Demand for bikes and docks dynamically changes throughout the day + season



Bike Management



Decision Event

Two scenarios:

- *Supply*: Too many bikes in the corresponding station
- *Demand*: Too few bikes in the corresponding station

Action

Indicate the station ID and:

- *Departure Station*: ID of source station of bikes
- *To Station*: ID of destination station
- *Number*: Quantity of bikes to move

Bike Management

The snapshot list / frame contains state information:

Event Payload

Previous events:

- *System Actions*: Whether bikes have been rebalanced or delivered between stations and their number
- *Demand Actions*: Trip information with pickup and dropoff location, and times

Station Details

For each station includes their ID and:

- *Bikes*: Current number of bikes
- *Capacity*: Maximum capacity
- *Extra Cost*: Whether station has extra fees associated

Weather information, holiday information, weekdays,

We will explore this first before
developing RL algorithms

Bike Management

×

By station/snapshot:

by_station

station index

3

0

447

Snapshot Sampling Ratio:

0.0

0.0

1.0

formula:

a+b



RUNNING...

Stop



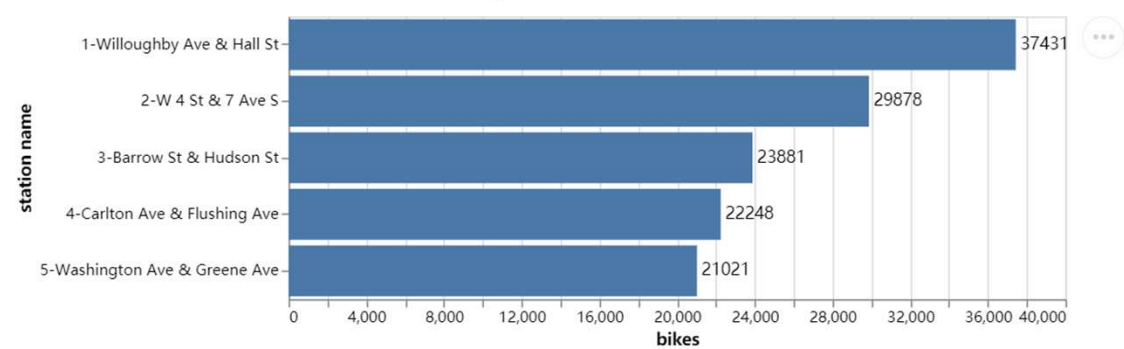
Citi Bike Intra Epoch Data

Cike Bike Top K

Select Top K



Top 5 bikes



Input Driven ('Exogenous') MDP

$$S = X \times \Xi$$

**State Space
Decomposition**

'Endogenous' (System
State) and 'Exogenous'
(Arrival State)



**System State (X) -
Capacity**



**Exogenous State (Ξ) -
Arrival**

Input Driven ('Exogenous') MDP

$$S = X \times \Xi$$

**State Space
Decomposition**

'Endogenous' (System
State) and 'Exogenous'
(Arrival State)



**System State (X) -
Capacity**

Current capacity at each
docking location, bikes
currently in transit, etc



**Exogenous State (Ξ) -
Arrival**

Current bike trip request

Plan for Today

Nonparametric RL

- “Nonparametric” function approximation
- Strong guarantees across:
Sample complexity, space complexity, storage complexity
- “Zooming dimension”

Tree-Partitions

- Implement tree-based adaptive discretization from nonparametric RL algorithms
- Use ORSuite to test on “continuous Ambulance routing”

Hindsight Learning

- Exogenous MDPs as model for OR problems
- Use of *Hindsight Planning* oracle for algorithm design
- Empirical results in VM allocation with Microsoft Azure

DeepRL for CitiBike

- Implement basic deepRL algorithms for CitiBike planning system
- Use MARO – Multi Agent Resource Optimization package from Microsoft Asia
- Visualizations!

Plan for Today

Understand Model

- Explore “topology” (aka scenarios)
- Explore “snapshot list” (aka state information)
- Develop + test heuristic greedy policy
- Look at implementation for Online LP based algorithm

DeepRL for CitiBike

- Implement basic Deep RL algorithms by implementing loss function
- Adjust “environment sampler” to interpret between business engine + policy models

References

[MARO]

- Documentation: <https://maro.readthedocs.io/en/latest/index.html>
- GitHub: <https://github.com/microsoft/maro/>

References

<https://github.com/seanrsinclair/RLinOperations>

