Deep Reinforcement Learning for Multi-Driver Vehicle Dispatching and Repositioning Problem

John Holler*†, Risto Vuorio*†, Zhiwei Qin‡, Xiaocheng Tang‡, Yan Jiao‡, Tiancheng Jin†,
Satinder Singh†, Chenxi Wang‡ and Jieping Ye‡
*Equal Contribution, †University of Michigan, ‡Didi Chuxing
{johnholl, riv, jintia, baveja}@umich.edu
{qinzhiwei, xiaochengtang, yanjiao, wangchenxi, yejieping}@didiglobal.com

***Abstract*—Order dispatching and driver repositioning (also known as fleet management) in the face of spatially and temporally varying supply and demand are central to a ride-sharing platform marketplace. Hand-crafting heuristic solutions that account for the dynamics in these resource allocation problems is difficult, and may be better handled by an end-to-end machine learning method. Previous works have explored machine learning methods to the problem from a high-level perspective, where the learning method is responsible for either repositioning the drivers or dispatching orders, and as a further simplification, the drivers are considered independent agents maximizing their own reward functions. In this paper we present a deep reinforcement learning approach for tackling the full fleet management and dispatching problems. In addition to treating the drivers as individual agents, we consider the problem from a system-centric perspective, where a central fleet management agent is responsible for decision-making for all drivers.**

***Keywords*-reinforcement learning, ride-sharing, fleet management, order dispatching**

I. Introduction

The order dispatching and fleet management system at a ride-sharing company must make decisions both for assigning available drivers to nearby passengers (hereby called orders) and for repositioning drivers who have no nearby orders. These decisions have short-term effects on the revenue generated by the drivers and driver availability. In the long term they change the distribution of drivers across the city, which in turn has a critical impact on how well future orders can be served. Provident algorithmic solutions, which account for the short term and long-term consequences of their decisions can improve the quality of service of the ride-sharing platforms and are thus an important area of research.

Recent works [1], [2] have successfully applied Deep Reinforcement Learning (RL) techniques to dispatching problems, such as the Traveling Salesman Problem (TSP) and the more general Vehicle Routing Problem (VRP) [3], however they have primarily focused on *static* (*i.e.* those where all orders are known up front) and/or *single-driver* dispatching problems. In contrast to these problems, the fleet management and order dispatching problem ride-sharing platforms face has multiple drivers and dynamically changing supply and demand conditions. We refer to this dynamic dispatching and fleet management problem as the Multi-Driver Vehicle Dispatching and Repositioning Problem (MDVDRP).

The planning problem presented by the MDVDRP is related to the VRPs, but the complexity comes from the dynamic nature of the assignment scenario rather than the intractability of computing the exact solution. Drivers and orders appear in the assignment system at random points in time. In this dynamic assignment setting, assignment decisions are made based on the current driver-order situation, without exact information about future orders. A high performing assignment solution needs to account for unknown future supply and demand conditions.

In realistic instances of the MDVDRP, the decision-making continues 24 hours a day and may involve thousands of drivers and tens of thousands of customers. Accounting for the spatially and temporally varying supply and demand conditions makes hand-crafting heuristic solutions to these scenarios challenging. In this paper, we explore a deep reinforcement learning approach to the MDVDRP. The contributions of our work can be summarized as follows. (i) We introduce a new reinforcement learning problem: the MDVDRP, which is motivated by the needs of real-world ride-sharing platforms. (ii) We propose a novel network architecture for decision-making in a realistic problem setting with variable sized observation and action spaces. (iii) We provide empirical analysis of value-based and actor-critic methods on instances of the MDVDRP, including instances based on real-world data.

II. Related Work

Recent machine learning approaches to dispatching and routing problems operate according to an encoding-decoding scheme, where information is first processed into a fixed-sized representation, and then actions are decoded from this representation [1], [4]. Pointer networks [5] offer an approximate solution to traveling salesman problems by encoding cities (in our terminology, orders) with a recurrent network, and then producing a solution by sequentially "pointing" to orders using an attention mechanism [6]. The network is trained with a supervised loss function by imposing a fixed ordering rule on decoded orders. Bello *et al.* propose training an architecture similar to the pointer networks with policy gradients instead of a supervised loss, which allows them to dispense with the fixed ordering of the outputs during the decoding phase [1]. Similarly, we use reinforcement learning to train our networks. We follow an architecture related to [2],

which uses an attention mechanism for encoding the inputs. We depart from their architecture in two ways. First, we replace the input attention layers with layers that compute their output elementwise. Second, we remove the recurrent network used in the decoder.

In practice, order dispatching and fleet management problems are often solved with heuristic solutions. [7]. In Local Policy Improvement [8], handcrafted heuristics are combined with a machine learning method by summarizing supply and demand patterns into a table and then using the learned patterns to account for future gains in the real-time planner of the dispatching solution. A fully machine learning based approach to the dispatching problem is presented in [9], where deep Q-learning is used for learning dispatching strategies from the perspective of a single driver. We take these developments a step further and learn fleet management and order dispatching strategies end-to-end using reinforcement learning.

Another thread of related work comes from the multi-agent reinforcement learning literature. Specifically, our single-driver training approach is analogous to the "independent Q-learning" training approach [10]. Multi-agent reinforcement learning has also been investigated for order dispatching in [11], where a grid-based algorithm is used and in fleet management in [12]. Instead of operating on a grid, our method is based on continuous coordinates, which makes it more ready for deployment in the real-world.

III. Method

A. MDVDRP as a Reinforcement Learning Environment

The experiments presented in this paper are conducted in a ride-sharing simulation environment. The environment is designed to capture the dynamic supply and demand situation in ride-sharing platforms. The environment represents customers as orders, which start and end in some coordinates. Assigning a driver to the order immediately yields a reward proportional to the price of the order. Drivers are represented as points in the 2-D space and they can move by serving orders or repositioning without an order. The drivers and orders are generated following a Poisson process with parameters depending on each scenario we consider.

Decision points are triggered whenever a driver becomes active in the system, finishes an order or finishes a repositioning action. Variable amounts of time may have passed between the decision points when the simulator polls the policy for actions. The simulation scenarios considered in the experiments mostly depict the situation where there are more customers demanding rides than there are drivers to serve them. In this setting, it is natural to assume that only a single driver is available for actions at any decision point. This assumption simplifies the design of the policies by removing the need to choose which driver to assign an order to. To prevent multiple drivers polling for actions at exactly the same moment, we add random noise with small variance to the duration of the reposition actions.

Assigning a driver to an order removes the order from the system and makes the driver unavailable for instructions until the order has been completed. At order completion the driver is relocated to the order destination and made available for assignments. Orders have a limited time window within which they are valid. After the validity window has passed, the orders will be removed from the system.

The policies may choose to move the drivers to different directions for a fixed amount of time by selecting reposition actions. The number of available reposition actions includes actions that move the driver into one of the eight cardinal directions for a fixed period of time and a stationary action.

The observation of the agents consists of the environment time, the driver for which action is currently being selected and all drivers and orders currently in the simulation. At time t there is a collection of orders $o_t^i \in \mathcal{O}_t$, drivers $d_t^j \in \mathcal{D}^t$, with exactly one *available driver* $d_t^{selected}$. The state is given to the neural network as $s_t = (\mathcal{O}_t, \mathcal{D}_t, d_t^{selected}, t)$. The orders are presented as 6 dimensional vectors consisting of the starting and ending coordinates, price, and time waiting. Time waiting is the difference between the current time and the creation time. A driver is represented by a 6 dimensional vector: the coordinates of the driver location, x and y components of its reposition direction, time to order completion, and time to reposition completion. If the driver is serving an order, its location is set to the ending location of the order it is servicing. If the driver is repositioning the driver location is updated at each timestep, the reposition direction shows which way the driver will move during the next timestep.

To limit the number of orders considered by the policy at each timestep, we impose a *broadcasting radius* d_{bcast} on the order assignment. This means that drivers may be only paired with orders if they are within d_{bcast} units of the driver. Otherwise, the driver may only take a repositioning action. The repositioning actions are not available to the drivers when there are orders within broadcasting radius of them.

B. Reward Settings

The objective of the algorithms in the MDVDRP problem is to maximize the cumulative reward defined by the environment. The environment rewards the agent for each assigned order with a reward the size of the order price. Reposition actions yield no reward. We consider two alternative reward specifications corresponding to *driver-centric* and *system-centric* perspectives. An visual overview of these concepts is presented in Figure 1

In the driver-centric approach, we consider the MDVDRP a reinforcement learning problem from the perspective of the individual driver. In this setting, each driver is maximizing their own expected revenue and there are no incentives for co-operation. The trajectories taken by each driver in the environment are collected separately and the discounted returns are computed on the individual trajectories. The individual trajectories consist of timesteps that are consecutive from the perspective of the driver but not necessarily from the perspective of the environment as other drivers may have taken actions between the actions of any single driver.

From the point of view of the ride-sharing platform, the dispatching and repositioning problem is not about individual

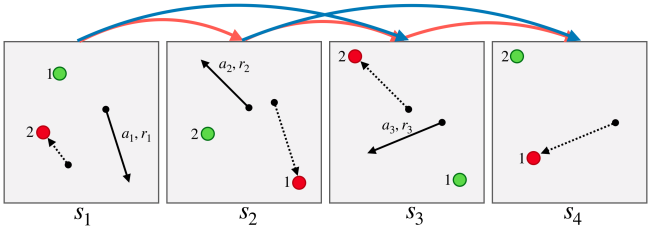


Fig. 1. The above image shows a trajectory with four timesteps in an MDVDRP instance with two drivers. The currently available driver is green, dispatched driver is red, and the order that the available driver accepts at time t is a_t and has price r_t. The accepted order at time t is labeled by its action name and price, (a_t, r_t) and travels from the solid black dot to the terminal arrow. Driver-centric transitions are indicated by blue arrows above state, e.g. transition (s_1, a_1, r_1, s_3), which is driver-centric with respect to driver 1. System-centric transitions are indicated by red arrows e.g. transition(s_1, a_1, r_1, s_2), which transitions from a state where driver 1 is available to a state where driver 2 is available.

drivers maximizing their own revenue but rather about the platform maximizing the combined revenue across all drivers. Therefore, it is important to consider optimizing the policies from the perspective of the whole system. In this system-centric approach, the expected cumulative reward across all drivers is being maximized. This leads to the trajectories experienced by the policy consisting of timesteps that are consecutive from the perspective of the environment. For example, if the driver i acts on the timestep t_1 receiving reward r_1 and driver j takes an action on the timestep t_2, the training algorithm will consider the timesteps t_1 and t_2 consecutive.

C. Neural Network Architecture

We propose a neural network architecture for RL in environments with variable sized observation and action spaces. An overview of the proposed network architecture is presented in Figure 2. A learned pooling mechanism allows the network to compute a fixed-sized global representation of the inputs, which enables relating the features of each individual input to the global state. In the environments we consider, the number of actions depends on the number of orders in the observation as described in III-A. We compute network outputs, one for each action, in a manner similar to the weight computation in the attention mechanism [6].

The network first computes order embeddings ν_o^i, order pooling weights α_o^i, driver embeddings ν_d^j, and driver pooling weights α_d^j. The embeddings are length 128 vectors computed by MLP_d^{emb} and MLP_o^{emb}, both of which have one hidden layer of size 128 and ReLU activations. The scalar pooling weights α are computed from the embeddings by MLP_d^w and MLP_o^w. Both have hidden layer size 128 and tanh activation, and sigmoid output activation. The global context vector is computed as $\left[\sum_{i=1}^{N} \alpha_o^i \nu_o^i | \sum_{j=1}^{M} \alpha_d^j \nu_d^j | \nu_d^{selected} | t\right]$, where $[a|b]$ denotes concatenation and t denotes time.

MLP^{assign}, which has one hidden layer of size 64 and ReLU activation, outputs values for the assignment actions. MLP^{assign} takes each order embedding concatenated with the global context separately as input and produces a scalar output for each input. The repositioning actions are computed

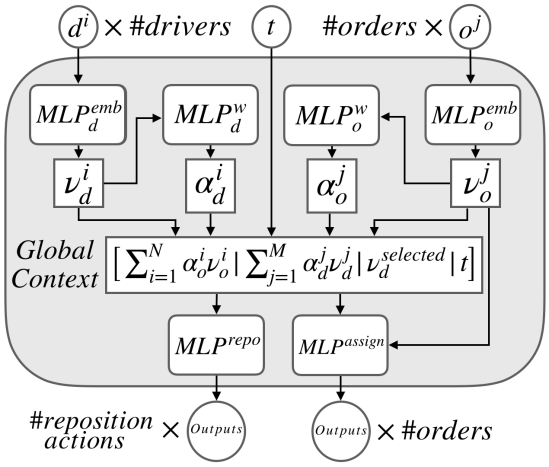


Fig. 2. Network Architecture. Driver and order embeddings ν_d^i, ν_o^j and their corresponding weights α_d^i, α_o^j are computed by MLP^{emb} and MLP^w respectively. A fixed sized global representation of the orders and drivers is computed by concatenating the sums of the weighted embeddings with the selected driver embedding and the environment time. The fixed number of outputs for the reposition actions are computed by MLP^{repo} using the global context as an input. MLP^{assign} computes one output for each order using the global context and each order embedding as an input.

by MLP^{repo} with the same architecture as MLP^{assign}. MLP^{repo} has one output for each reposition action and uses the global context as its input.

D. Training Algorithms

We train the proposed network architecture on the MDVDRP using two modern reinforcement learning algorithms: Deep Q-Networks (DQN) [13] and Proximal Policy Optimization (PPO) [14]. We chose these two algorithms because they represent widely used, modern methods in off-policy and on-policy reinforcement learning. Many of the recent successes in deep reinforcement learning have been achieved using one of the two algorithms. DQN is a value-based, off-policy reinforcement learning algorithm. PPO is an on-policy actor-critic reinforcement learning algorithm. For information about the differences of on-policy versus off-policy and value-based versus actor-critic methods, we point the reader to [15]. For detailed descriptions on the DQN and PPO algorithms we direct the reader to the respective papers.

As the simulation runs in continuous time, the time between consecutive timesteps may vary. Both algorithms use a discounting factor γ to compute the discounted return, which accounts for the future rewards. In continuous time settings, the discounting factor for each timestep is $\gamma^{t'-t}$, where t is the time at the current observation and t' in the next.

We found empirically that training using the system-centric rewards is more challenging than using the driver-centric rewards. We found the use of n-step Q-learning [16] helpful for stabilizing the training of DQN when training on system-centric rewards. In all of our DQN experiments with system-centric reward we use 20-step Q-learning.

TABLE I

EXPERIMENTAL RESULTS. THE ALGORITHMS WERE EVALUATED MULTIPLE TIMES DURING THE TRAINING AT FIXED INTERVALS AND THE RESULTS OF THE BEST EVALUATION STEP ACROSS ALL RANDOM SEEDS IS REPORTED $\pm$ STANDARD ERROR. THE REPORTED VALUES ARE AVERAGES OVER 5 EPISODES FOR HOT COLD AND REGIONAL DOMAINS AND OVER 20 EPISODES FOR HISTORICAL ORDERS DOMAIN. ALL THE SCORES THAT ARE WITHIN STANDARD ERROR OF THE BEST SCORE ARE BOLDED IN THE TABLE.

	Hot Cold		Regional		Historical Orders
Algorithm	High Demand	Low Demand	High Demand	Low Demand	
MRM-simple	5359 ± 8	5189 ± 14	3597 ± 6	2964 ± 22	40001 ± 128
MPDM-simple	5917 ± 6	5713 ± 20	4258 ± 8	3328 ± 28	37960 ± 127
MRM-random	797 ± 30	949 ± 41	2150 ± 30	3039 ± 30	49563 ± 309
MPDM-random	1006 ± 35	1004 ± 50	4203 ± 19	3103 ± 33	46763 ± 241
MRM-demand	5351 ± 9	5449 ± 9	2161 ± 28	3262 ± 16	48805 ± 463
MPDM-demand	5883 ± 17	5658 ± 15	4252 ± 8	$\mathbf{3343 \pm 16}$	46635 ± 539
PPO System-Centric	$\mathbf{7954 \pm 17}$	5801 ± 29	4744 ± 2	$\mathbf{3372 \pm 33}$	50094 ± 162
DQN System-Centric	6323 ± 168	5278 ± 77	4735 ± 12	2831 ± 104	48532 ± 71
PPO Driver-Centric	7861 ± 23	5767 ± 10	4888 ± 2	3208 ± 16	53029 ± 45
DQN Driver-Centric	7883 ± 3	$\mathbf{5855 \pm 8}$	$\mathbf{5006 \pm 15}$	$\mathbf{3349 \pm 6}$	$\mathbf{53255 \pm 130}$

IV. EXPERIMENTS

We investigate the learning behavior of the proposed network architecture in ride-sharing environments implemented using the simulator described in III-A. We present results in four environments to test and illustrate the dispatching and repositioning strategies learned by the proposed approach. In all environments, the geography is presented as a rectangle with the longer side length set to one. The drivers move at speed 0.1 and the broadcasting radius is set to 0.3. The parameters specific to each environment are described in their respective sections.

We compare the learned policies against two kinds of baselines: myopic revenue maximization (MRM) and myopic pickup distance minimization (MPDM) [7]. MRM always assigns the highest value order to the closest available driver. MPDM assigns orders to drivers in the order of shortest distance first. Since the baselines do not account for repositioning, we test three variants of the baselines with different repositioning heuristics. In the *simple* variants, broadcasting distance is ignored and drivers can be assigned to orders across the region. The drivers stay where they drop orders off until they are assigned to the next order. In the *random* variants of MRM and MPDM, if a driver has no orders within broadcast distance, then a repositioning action is selected randomly. The *demand* variants of MRM and MPDM apply a simple heuristic on repositioning, by moving the drivers towards the nearest order when an order is available but not within broadcasting distance. If there is no order available, the demand variants take random reposition actions.

We use the same neural network architecture for all variants of the learning algorithms, except for the extra output layer implementing the critic for PPO. We set the discount factor $\gamma = 0.99$ for both algorithms. For DQN we use batch size of 32, replay buffer size 20000 and update on every timestep with learning rate 0.0001. The exploration rate ϵ starts from 0.99 and we anneal it by 0.01 on each episode to the final value 0.1. We update the target network every 100 steps. The PPO policy and value functions are updated 20 times every epoch using 4000 consecutive timesteps as the training data. We aim to keep hyperparameters unchanged between the different environments but make slight changes for Distribute Domain and the real data based domain. Those changes are explained in the relevant sections. The results from the experiments can be found in Table I and within the following sections.

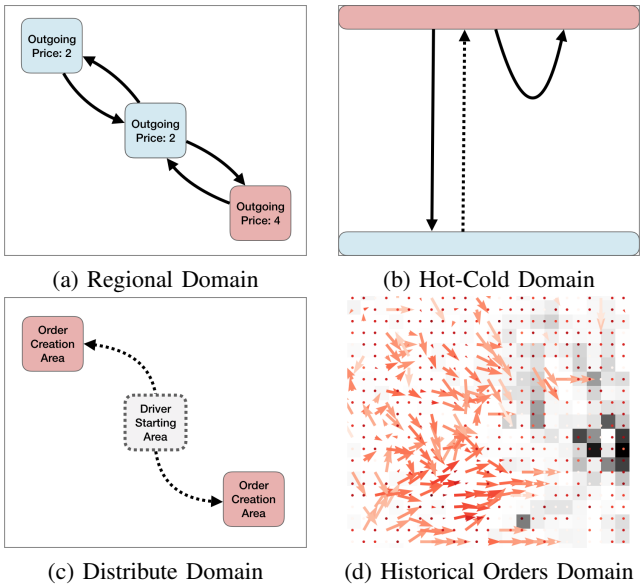
A. Regional Domain

In our first experiment, we consider the Regional Domain, which illustrates how a simple price differential can be exploited by learned policies but is missed by the myopic dispatching and repositioning approaches. Intuitively, in this domain, a good policy dedicates enough drivers to fully serve the high-reward orders and serves the other orders with the remaining drivers. In the Regional Domain, there are three regions: left, center, and right. Equal numbers of orders are generated between each pair of adjacent regions. All orders yield a reward of 2 except those that go from right to center, which yield a reward of 4. The high-level concept of the domain is presented in Figure 3.

In the high demand version of the Regional Domain, the best learned policy (Driver-Centric DQN) outperforms the best performing baseline (MPDM-demand) by over a 15% margin. The low demand variant proves to be challenging for the learning algorithms. Here the demand is low enough that over commitment to the high reward area can become a problem as is the case for Driver-Centric PPO, which ends up allocating 8 times more idle drivers to the high reward area and as a consequence has 8% lower ratio of total orders served compared to MPDM-demand. This policy leads to a weak performance, and is in fact outperformed by the simple and demand variants of MPDM.

B. Hot-Cold Domain

The Hot-Cold domain can be thought of as a ride-sharing scenario with a busy area of downtown ("hot region") surrounded by suburbs with less traffic ("cold region"). Order pickup locations are located uniformly along the top edge of the simulation area. Half of the orders end uniformly along



(a) Regional Domain (b) Hot-Cold Domain

(c) Distribute Domain (d) Historical Orders Domain

Fig. 3. Conceptual drawings of the illustrative domains considered in the experiments. The colored regions represent areas where orders are generated. The solid arrows depict order starting and ending locations and the dotted paths depict paths the drivers need to reposition along in order to get to the orders. Best viewed in color. (a) **Regional domain** tests whether the policies can learn to exploit price differences between otherwise similar orders. Each square is labeled with its outgoing order value. (b) **Hot-Cold Domain** seeks to evaluate the algorithms ability to learn allocating drivers to orders which minimize driver idle time. All orders begin in the red bar, with their positions generated uniformly randomly. For the destination, a fair coin is flipped to decide whether the order ends in hot or cold, and then the exact position is sampled uniformly randomly in the designated region. (c) **Distribute Domain** requires the policies to anticipate that the orders are going to be created in the two distant regions and allocate correct number of drivers to each. Figure (d) represents an order generation pattern defined by the historical data and the corresponding reposition strategy learned by the policy for an hour long time window in **Historical Data Domain**. The graph is composed of 2d histogram depicting the order generation pattern and arrow plots depicting the average reposition movements in each histogram bin. The intensity of the arrow color corresponds to the number of drivers who have been in each cell during the time window.

the bottom edge of the area and half end uniformly in the hot region. Order price is given by the distance between order pickup and drop-off locations. Despite orders to the cold region having higher prices, it is generally more advantageous for drivers to stay in the hot region, since there they can quickly pick up new orders. In other words, the advantage is entirely *temporal*. An illustration of the Hot-Cold domain is presented in Figure 3.

The results in Table I suggest that learning to balance serving the orders to hot and cold regions is straightforward for the learning algorithms and all learning algorithms outperform all baselines in the high demand variant of the environment. As with the Regional domain, the challenges of training DQN with system-centric rewards are apparent in the low demand Hot-Cold domain, where it is outperformed by multiple baselines.

In all of the experiment configurations for Regional domain and Hot-Cold domain, we found DQN to be more sample efficient than PPO. DQN was trained for 1000 episodes and PPO often took two to three times as many to achieve similar performance. On-policy methods are known to be less sample efficient than off-policy methods and another contributing factor may be the relatively low learning rate we used for PPO.

TABLE II
DISTRIBUTE DOMAIN WITH 20 DRIVERS. THE COLUMNS CORRESPOND TO TWO INSTANCES OF THE DISTRIBUTE DOMAIN. ONE WITH A UNEVEN 80/20 SPLIT OF ORDERS BETWEEN THE PATCHES AND THE OTHER WITH AN EVEN SPLIT.

Algorithm	50/50 Served %	80/20 Served %
Optimal	100%	100%
Uniform Optimal	50%	80%
PPO System-Centric	$100 \pm 0.0\%$	$93 \pm .54\%$
DQN System-Centric	$95 \pm .11\%$	$80 \pm 3.42\%$
PPO Driver-Centric	$96 \pm .13\%$	$92 \pm .72\%$
DQN Driver-Centric	$96 \pm .13\%$	$92 \pm .72\%$

C. Distribute Domain

While Hot-Cold domain tests an important aspect of learning - namely, the ability of the agents to reposition drivers to locations where they can pick up new orders, this repositioning behavior is quite simple in that it is *uniform across drivers*. In order to test whether our methods can learn non-uniform repositioning behavior, we introduce "distribution environments" where drivers must be repositioned so as to match their spatial distribution with a fixed future order distribution. A distribution environment operates in two phases. In the first phase, the environment resets to a state with k drivers and no orders, so drivers may only reposition during this phase. In the second phase, k orders appear according to a fixed spatial distribution. Each order matching action receives $+1$ reward. Order destinations are placed away from start locations so that each driver may only serve one order per episode. As a result, the episodic return is proportional to the number of orders served, so we may interpret the episode score as a measure of how well the agent arranges driver supply in phase 1 with order demand in phase 2. In our experiments, the distribution of orders always consists of two small patches in the top left and bottom right parts of the unit square. Refer to Figure 3 for visualization. The order start locations are sampled uniformly within each patch.

We found that training successful policies on the Distribute Domains requires more random exploration than any of the other environments. For DQN, we set the final $\epsilon = 0.2$. For PPO, we follow an annealing scheme similar to DQN where we anneal the entropy coefficient from 0.7 to 0.01 over the first 2000 epochs.

Results for distribute domains with 20 drivers are presented in Table II. We include the optimal served percentage (which is 100 %) and the "uniform optimal" served percentage. This quantity reflects the maximum score one can obtain if the repositioning behavior is uniform across drivers. The results between driver and system-centric variants are mixed. While system-centric PPO achieves a slight advantage over the driver-centric variant, the relationship is flipped for DQN.

D. Historical Orders Domain

Solving the MDVDRP is motivated by the real-world need of ride-sharing platforms to improve their marketplace for drivers and passengers. To test our learning algorithms in a more realistic setting, we consider an environment where the order generation scheme is based on historical order data from the GAIA dataset [17]. The dataset provides GPS records for all orders served during a 30-day period in the city of Chengdu in China. To limit computational demands, we choose a subset of 10% of the orders in the dataset. The orders in the subset all start and end in an area from the dataset that has approximately twenty thousand orders per day. We then create 30 *order generation schemes*, which correspond to the 30 days in the dataset. Each episode in the environment corresponds to a randomly sampled day from the dataset. The orders generated during the episode appear exactly in the coordinates and at the time defined by the data. We use a fixed number of drivers (100), a 2 kilometre broadcast radius and a fixed speed (40 km/h).

Similarly to the Hot-Cold domain, the reward for serving an order is the distance from the order start location to the drop-off location. Following from the reward definition, the total reward each driver receives is directly correlated with the total time they spend serving orders and thus inversely correlated with the time spend waiting for orders and picking up orders.

Driver-centric DQN and PPO are both capable of learning strong dispatching and repositioning policies, which outperform all of the baselines by over 6%. The historical data domain also demonstrates the importance of redistributing drivers during their downtime. The worst performing algorithms on the historical data domain are the *simple variants* of MPDM and MRM, which do not use reposition actions at all. In contrast, the learned policies actively redistribute drivers back to the populated areas as shown in Figure 3.

Finally, we observe that both DQN and PPO have trouble learning competitive policies on this larger scale problem when trained on the system-centric rewards. We hypothesize that this is due to having more drivers complicating the already challenging credit assignment problem. With more drivers simultaneously acting in the environment, the time between decision points becomes smaller and the effective discount factor approaches one. Training with a discount factor close to one can make the training unstable. To mitigate this effect we use a smaller base discount factor $\gamma = 0.9$.

V. Conclusion

We performed a detailed empirical study of reinforcement learning approaches to multi-driver vehicle dispatching and repositioning problems. We studied driver-centric and system-centric reward definitions and trained policies using DQN and PPO algorithms. We found DQN to be more sample efficient than PPO. On the other hand PPO was better able to learn on system-centric rewards. Central to all of our approaches was the network architecture we presented, which leverages a global representation of state processed using attention mechanisms. We found that, while one can construct environments where the system-centric approach is superior, typically driver-centric is better or at least competitive with the system-centric approach. Furthermore we applied these methods to environments built using real dispatching data, and found that driver-centric approach is able to consistently beat myopic dispatching and repositioning strategies.

References

[1] I. Bello, H. Pham, Q. V. Le, M. Norouzi, and S. Bengio, "Neural combinatorial optimization with reinforcement learning," *arXiv preprint arXiv:1611.09940*, 2016.

[2] M. Nazari, A. Oroojlooy, L. Snyder, and M. Takac, "Reinforcement learning for solving the vehicle routing problem," in *Advances in Neural Information Processing Systems 31*, S. Bengio, H. Wallach, H. Larochelle, K. Grauman, N. Cesa-Bianchi, and R. Garnett, Eds. Curran Associates, Inc., 2018, pp. 9839–9849. [Online]. Available: http://papers.nips.cc/paper/8190-reinforcement-learning-for-solving-the-vehicle-routing-problem.pdf

[3] G. B. Dantzig and J. H. Ramser, "The truck dispatching problem," *Management science*, vol. 6, no. 1, pp. 80–91, 1959.

[4] M. Deudon, P. Cournut, A. Lacoste, Y. Adulyasak, and L.-M. Rousseau, "Learning heuristics for the tsp by policy gradient," in *Integration of Constraint Programming, Artificial Intelligence, and Operations Research*, W.-J. van Hoeve, Ed. Cham: Springer International Publishing, 2018, pp. 170–181.

[5] O. Vinyals, M. Fortunato, and N. Jaitly, "Pointer networks," in *Advances in Neural Information Processing Systems*, 2015, pp. 2692–2700.

[6] V. Mnih, N. Heess, A. Graves *et al.*, "Recurrent models of visual attention," in *Advances in neural information processing systems*, 2014, pp. 2204–2212.

[7] L. Zhang, T. Hu, Y. Min, G. Wu, J. Zhang, P. Feng, P. Gong, and J. Ye, "A taxi order dispatch model based on combinatorial optimization," in *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*. ACM, 2017, pp. 2151–2159.

[8] Z. Xu, Z. Li, Q. Guan, D. Zhang, Q. Li, J. Nan, C. Liu, W. Bian, and J. Ye, "Large-scale order dispatch in on-demand ride-hailing platforms: A learning and planning approach," in *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. ACM, 2018, pp. 905–913.

[9] Z. Wang, Z. Qin, X. Tang, J. Ye, and H. Zhu, "Deep reinforcement learning with knowledge transfer for online rides order dispatching," in *2018 IEEE International Conference on Data Mining (ICDM)*. IEEE, 2018, pp. 617–626.

[10] C. Claus and C. Boutilier, "The dynamics of reinforcement learning in cooperative multiagent systems," in *Proceedings of the AAAI conference on artificial intelligence*, vol. 1998, 1998, pp. 746–752.

[11] M. Li, Z. Qin, Y. Jiao, Y. Yang, Z. Gong, J. Wang, C. Wang, G. Wu, J. Ye *et al.*, "Efficient ridesharing order dispatching with mean field multi-agent reinforcement learning," 2019.

[12] T. Oda and C. Joe-Wong, "Movi: A model-free approach to dynamic fleet management," in *IEEE INFOCOM 2018-IEEE Conference on Computer Communications*. IEEE, 2018, pp. 2708–2716.

[13] V. Mnih, K. Kavukcuoglu, D. Silver, A. A. Rusu, J. Veness, M. G. Bellemare, A. Graves, M. Riedmiller, A. K. Fidjeland, G. Ostrovski *et al.*, "Human-level control through deep reinforcement learning," *Nature*, vol. 518, no. 7540, p. 529, 2015.

[14] J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov, "Proximal policy optimization algorithms," *arXiv preprint arXiv:1707.06347*, 2017.

[15] R. S. Sutton and A. G. Barto, *Introduction to Reinforcement Learning*, 1st ed. Cambridge, MA, USA: MIT Press, 1998.

[16] V. Mnih, A. P. Badia, M. Mirza, A. Graves, T. Lillicrap, T. Harley, D. Silver, and K. Kavukcuoglu, "Asynchronous methods for deep reinforcement learning," in *International conference on machine learning*, 2016, pp. 1928–1937.

[17] Didi Chuxing, "Didi launches gaia initiative to facilitate data-driven research in transportation," URL: http://www.didichuxing.com/en/press-news/bgcitgfc.html, 2017.