Deep Surrogate Q-Learning for Autonomous Driving

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Abstract—Open challenges for deep reinforcement learning systems are their adaptivity to changing environments and their efficiency w.r.t. computational resources and data. In the application of learning lane-change behavior for autonomous driving, the number of required transitions imposes a bottleneck, since test drivers cannot perform an arbitrary amount of lane changes in the real world. In the off-policy setting, additional information on solving the task can be gained by observing actions from others. While in the classical RL setup this knowledge remains unused, we use other drivers as surrogates to learn the agent’s value function more efficiently. We propose Surrogate Q-learning that deals with the aforementioned problems and reduces the required driving time drastically. We further propose an efficient implementation based on a permutation equivariant deep neural network architecture of the Q-function to estimate action-values for a variable number of vehicles in sensor range. We evaluate our method in the open traffic simulator SUMO and learn well performing driving policies on the real highD dataset.

I. INTRODUCTION

For high-level decision making, many autonomous driving systems use pipelines comprised of modular components for perception, localization, mapping, motion planning and the decision component itself. In recent years, Deep Reinforcement Learning (DRL) has shown promising results in various domains \cite{1}, \cite{2}, \cite{3}, and in the application of high-level decision making in autonomous driving \cite{4}, \cite{5}, \cite{6}, \cite{7}, \cite{8}, \cite{9}. However, there remain a lot of challenges that are limiting w.r.t. the implementation of DRL for such components on real physical systems. Besides others, the following properties have to be ensured:

1) Generalization: The system has to generalize to new situations. Since classical rule-based decision-making modules are limited in their generalization abilities, DRL methods offer a promising alternative for this component due to their ability to learn policies from previous experiences. Nonetheless, generalization has to be improved by using suitable deep network architectures.

2) Adaptivity: The system has to deal with changing environments and a varying number of traffic participants.

3) Efficiency: Computational and data-efficiency are restrictive bottlenecks, i.e. the number of required lane-changes of the test vehicle in the training set. While in simulation it is possible to collect data with policies performing as many lane-changes as possible \cite{6}, \cite{7}, in real scenarios test drivers cannot perform that many lane-changes. This restriction leads to a tremendous increase in demand of recordings.

A well-performing flexible architecture for the action-value function that can deal with a variable-sized input list was already proposed in the DeepSet-Q approach \cite{6} for this domain. The architecture tackles already two of the three above mentioned challenges: generalization and adaptivity. The algorithm, employing the formalism of Deep Sets \cite{11}, is able to deal with a variable number of surrounding vehicles as an extension of DQN to estimate the action-value function for the agent. This approach outperformed DQN agents with fully-connected networks using fixed-sized input representations \cite{12}, \cite{4}, \cite{5}, \cite{13}, \cite{14} or CNNs in combination with occupancy grids \cite{15} or CNNs. DeepSet-Q was able to learn a comfortable and robust driving policy with a transition set of \( \sim 270 \) driving hours in simulation. In \cite{7}, the input representation based on Deep Sets was extended to deal with graphs in the interaction-aware Graph-Q algorithm.

For implementation on real physical systems, however, there remains the challenge of building an efficient system while staying adaptive to a changing environment and generalizable to unseen situations. In the domain of autonomous driving, the representation of the environment comprises of an agent, performing actions and collecting data, and a list of surrounding traffic participants, each acting w.r.t. their own respective value-function but...
within the same high-level action space. The classical RL formulation, only considering the agent’s transitions, can be improved by exploiting that recorded transitions contain collections of all vehicles in sensor range, and actions and rewards of all vehicles can be inferred for consecutive time steps using the reward function of the ego-car agent (not the actual, unknown rewards of the other participants). Hence, all transitions of all vehicles can be leveraged via off-policy reinforcement learning (RL) in order to optimize a value-function subject to the reward function of the agent, which we call Surrogate Q-learning. Taking into account actions of all surrounding drivers reduces the required driving time to collect the same amount of lane-changes tremendously. While in the classical RL setup, this additional knowledge about task execution remains unused, in this setting, a policy can even be learned without performing any lane-changes with the test vehicle itself or by recording images from drones or bridges.

The key aspect of Surrogate Q-learning is a flexible permutation equivariant deep neural network architecture to estimate the action-value function with DQN efficiently, as shown in Figure 1. A permutation equivariant architecture computes for a list of input vectors an equally-sorted and equally-sized list of output vectors. The architecture makes use of transitions of all participants in sensor range in parallel, leading to maximum data- and runtime-efficiency. The network is able to deal with a variable-sized list of inputs, equal to the current number of vehicles in sensor-range and outputs a variable-sized list of output vectors of the same size simultaneously, here corresponding to Q-values for every vehicle in the scene. Since these values are estimated by the same Q-approximation network, the additional transitions help to speed up learning of the action-value estimation of the agent drastically.

By taking all actions from all participants in a sample into account for one respective update, Surrogate Q-learning inherently encompasses a unique way of replay sampling. Informed sampling from the replay buffer has been first discussed in [17], where transitions in the replay-buffer are drawn according to a ranking on the basis of current TD-error. Surrogate Q-learning, on the other hand, implements a sample distribution dependent on the complexity of the scene, i.e. the number of vehicles and takes full advantage of the given sample set without an increase in computation time.

Our main contributions are threefold: First, we propose Surrogate Reinforcement Learning which makes use of transitions of all vehicles to generate more actions and rewards by evaluating all other vehicles with the reward function of the agent, as described in Figure 2 and formalize the Surrogate Q-learning algorithm. Second, we introduce a novel flexible permutation equivariant network architecture to estimate Q-values for all vehicles in sensor-range efficiently in parallel. Third, we evaluate the performance in the open-source traffic simulator SUMO and furthermore train on the open real highD dataset containing top-down recordings of German highways, which is an important step towards the application on a real system.  

II. REINFORCEMENT LEARNING

We model the task of learning lane-change behavior in autonomous driving as a Markov Decision Process (MDP), where the agent is acting with policy \( \pi \) in a highway environment. In state \( s_t \in S \), the agent applies a discrete action \( a_t^{\text{agent}} \in A \) and reaches a successor state \( s_{t+1} \sim M \) according to a transition model \( M \). In every time step \( t \), the agent receives a reward \( r_t^{\text{agent}} \) for driving comfortably and as close as possible to a desired velocity and tries to maximize the expectation of the discounted long-term return \( R(s_t) = \sum_{t=0}^\infty \gamma^{t-s} r_t \), where \( \gamma \in [0, 1] \) is the discount factor. The Q-function \( Q^{\pi}(s_t, a_t) = \mathbb{E}_{s_{t+1} \sim \pi}[R(s_t)|a_t] \) represents the value of following a policy \( \pi \) after applying action \( a_t \). The optimal value-function and optimal policy for a given MDP can then be found via Q-learning [18].

III. SURROGATE Q-LEARNING

We consider tasks in complex and stochastic environments where our agent acts among other participants, each following their own respective policy simultaneously. The set of participants in a scene \( s_t \) at time point \( t \) is denoted as \( \mathcal{P}(s_t) = \{\text{agent}, 1, \ldots, N(s_t)\} \), where \( N(t) \) is equal to the

![Fig. 2: Scheme of Deep Surrogate Q-Learning for the application of autonomous lane-changes. The agent (blue) and surrounding vehicles (white) act in a highway scenario. Exploiting off-policy Q-learning, transitions of all participants can be used to update the agent’s Q-function w.r.t the agent’s reward function, even if they have different goals and reward functions. The transition set is excluded from top down recordings of German highways in the open-source HighD dataset [10].](image-url)
number of surrounders in sensor-range of the agent. We assume that all surrounders have the same action space $\mathcal{A}$ as the agent or actions that are mappable to the agent’s action space. Our aim is to optimize the behavior of the agent according to its own reward function, but using additional surrogate reward function. This is possible whenever the agent can detect or infer actions of its surrounders. Based on the agent’s reward function, we can estimate the long-term value $Q(s_t, a_t^p|\theta, \rho)$ for the action executed by participant $p \in \mathcal{P}(s_t)$. Weights $\theta$ are parameters of the value-function approximation. The final policy of the agent can be extracted by:

$$\pi(s_t) = \arg \max_{a \in \mathcal{A}} Q(s_t, a|\theta, \rho).$$

In Deep Surrogate Q-learning, we use DQN to learn the optimal policy $\pi$ and fill a replay buffer $\mathcal{R}$ with scene-transitions $\mathcal{R}_i = \{(s_i, a_i, s_{i+1}, r_i)\}$ Naively, a new replay buffer $\mathcal{R}'$ could be created by $\mathcal{R}' = \bigcup_{\mathcal{R}_i \in \mathcal{R}} \beta(\mathcal{R}_i)$ with a projection function $\beta(\mathcal{R}_i) = \{\{s_i, a_i', s_{i+1}, r''_i\} | \forall p \in \mathcal{P}(s_t)\}$ and minibatches could be sampled uniformly from $\mathcal{R}'$ to update the Q-values. Instead, Surrogate Q-learning implements a novel experience replay sampling technique, which focuses on the complexity of a scene. To implement it efficiently, we introduce a novel permutation equivariant architecture capable of estimating multiple action-values at once, as detailed below.

In this setup, we define the complexity of a scene to be proportional to the number of surrounders. Intuitively, navigation in scenes with many close surrounders can be much more complicated than in empty spaces. From every scene-sample $\mathcal{R}_i$, a minibatch $\mathcal{B}$ of size $m$, a further batch of samples can be generated via a projection function $\beta^{\mathcal{B}}$, which extracts a batch of transitions of all participants in the scene:

$$\beta^{\mathcal{B}}(\mathcal{R}_i) = \{\{(s_i, a_i', s_{i+1}, r''_i)\} | \forall p \in \mathcal{P}(s_t)\}.$$ 

To update the action-value function, we then create a batch of virtual samples by concatenation of the projected batches:

$$B^{\text{virtual}} = \bigcup_{1 \leq i \leq m} \beta^{\mathcal{B}}(\mathcal{R}_i).$$

The size of the virtual batch can then be computed by $|B^{\text{virtual}}| = \sum_{1 \leq i \leq m} N(s_i)$. We sample minibatches of $\mathcal{R}$ uniformly with $\kappa_i \sim \mathcal{R}$, which means that the proportion of a scene in the virtual batch is larger the more surrounders are in the given scene. The optimization of Surrogate-Q is then formalized as:

$$\min_{\theta} E_{B^{\text{virtual}} \sim \mathcal{R}} \left[ \sum_{(s_i, a_i^p, s_{i+1}, r''_i) \in \mathcal{B}^{\text{virtual}}} (y_i^p - Q(s_i, a_i^p|\theta, \rho))^2 \right],$$

with targets $y_i^p = r_i^p + \gamma \max_{a \in \mathcal{A}} Q'(s_{i+1}, a|\theta', \rho)$, where $Q'$ is a target network with parameters $\theta'$.

While execution of the learned policy is fast and efficient, computation requires multiple forward-passes per sample for classical deep neural network architectures, such as fully-connected neural networks or DeepSets. Depending on the number of surrounders, the runtime lies in $O(b \times m \times n)$ with $n = \max_{s_i \in \mathcal{R}} N(s_i)$ for replay buffer $\mathcal{R}$ and the number of sampled batches $b$. To reduce runtime, we describe an efficient permutation equivariant architecture in Section IV, which calculates Q-values for all participants in a scene in parallel, resulting in a runtime of $O(b \times m)$.

IV. EFFICIENT SURROGATE Q-LEARNING VIA PERMUTATION EQUIVARIANT Q-NETWORKS

We use a permutation equivariant architecture to estimate the action-value function of the agent efficiently. A permutation equivariant architecture can more formally be defined as a function $f : X^M \rightarrow Y^M$ that keeps the input permutation for the output, i.e. for any permutation $\pi$:

$$f([x_{\pi(1)}, \ldots, x_{\pi(M)}]) = [f_{\pi(1)}(x), \ldots, f_{\pi(M)}(x)].$$

Similar as in [6, 7], the architecture is able to deal with a variable number of input elements. The action-value representation is represented with a deep neural network $Q_{\text{SUR}}(\cdot, \cdot|\theta, \rho(\cdot))$, parameterized by weights $\theta, \rho_{\text{SUR}}$, and optimized via DQN. The network, consisting of three network modules $(\phi, \rho, Q)$, outputs a vector of action values for all participants $\mathcal{P}$ of the current scene, where architectural choices follow the derivations of the permutation equivariant case in [11]. The input layers are built of two neural networks $\phi$ and $\rho$, which are components of the Deep Sets [11], similarly used as in the work of [6] to deal with a variable input. The representation of the input scene $s_t$ is computed by:

$$\Psi(s_t) = \rho \left( \sum_{x^i_t \in s_t} \phi(x^i_t) \right),$$

resulting in a permutation invariant representation of the scene at time step $t$. In this work, we combine this scene-representation, concatenate it with features of the participants, and feed the resulting latent vector to the $Q$ module. Every output is the Q-value corresponding to one vehicle in the scene. More formally, the list of Q-values $q_t = [q_t^{\text{agent}}, q_t^1, \ldots, q_t^{N(s_t)}]$ is calculated as:

$$q_t = Q_{\text{SUR}}(s_t, a_t|\theta, \rho(s_t)).$$
Algorithm 1: Deep Surrogate Q-Learning via permutation equivariant Q-Networks

\begin{algorithm}
\begin{algorithmic}[1]
\State Initialize $Q_{\text{SUR}} = (\phi, \rho, Q)$ and $Q_{\text{SUR}}' = (\phi', \rho', Q')$
\State set replay buffer $\mathcal{R}$
\For{optimization step $o=1,2,...$}
\State get minibatch $\mathcal{B}_{\text{virtual}}$ from $\mathcal{R}$
\ForAll{$(s_t, a_t, s_{t+1}, r_t)$ in $\mathcal{B}_{\text{virtual}}$}
\State vehicle $x_{t+1}^j$ in $s_{t+1}$ do
\State $\phi' + 1 = \phi'(x_{t+1}^j)$
\State $\Psi'(s_{t+1}) = \rho' \left( \sum_j \phi' + 1 \right)$
\EndFor
\State vehicle $x_{t+1}^j$ in $s_{t+1}$ do
\State $y_t^j = r_t^j + \gamma \max_{a} Q'(\Psi(s_{t+1}), x_{t+1}^j, a)$
\EndFor
\State perform a gradient step on loss:
\State $\frac{1}{n} \sum_{j} \left( y_t^j - Q_{\text{SUR}}(s_t, a_t^j) \right)^2$
\State update target network by
\State $\theta_{Q_{\text{SUR}}'} \leftarrow \tau \theta_{Q_{\text{SUR}}} + (1-\tau) \theta_{Q_{\text{SUR}}'}$
\EndFor
\State get current state $s_t$ from environment
\State apply $a^\text{agent} = \arg \max_a Q_{\text{SUR}}(s_t, a)$
\Endalgorithmic}
\end{algorithm}

for every vehicle $p \in \{\text{agent}, 1, ..., N(s_t)\}$, as demonstrated in Figure 1. We choose $\epsilon(\Psi(s_t), x_t^p) = [\Psi(s_t)||x_t^p]$ to be the concatenation of participant features $x_t^p$ and the combined scene representation, leading to a prediction of the action-value for every participant. During runtime, the optimal policy of the agent can be extracted by:

$$\pi(s_t) = \arg \max_a q_t^a_{\text{agent}}.$$ 

The scheme of the network architecture is shown in Figure 1. The Q-function is trained on virtual minibatches $\mathcal{B}_{\text{virtual}}$ as described in Algorithm 1.

V. EXPERIMENTS

We formalize the task of performing autonomous lane changes as an MDP. The state space consists of relative distances, relative velocities and relative lanes for all vehicles within the maximum sensor range of the vehicle. As action space, we consider a set of discrete actions $A$ in lateral direction, including keep lane, perform left lane-change and perform right lane-change. Acceleration is handled by a low-level execution layer with model-based control of acceleration to guarantee comfort and safety. We use RL to optimize the long-term return, for which model-based approaches are limited in this domain. Collision avoidance in lateral direction and maintaining safe distance in longitudinal direction are controlled by an integrated safety module, analogously to [16], [5], [6]. For unsafe actions, the agent keeps the lane. We define the reward function as:

$$r^\text{agent}(s_t, a^p, s_{t+1}) = 1 - \frac{|v_t^p - v_{\text{desired}}|}{v_{\text{desired}}} - p_{\text{he}}(a^p),$$

where $v_t^p$ is the current velocity of participant $p$ and $p_{\text{he}} = 0.01$ if action $a^p$ is a lane change and 0 otherwise. The weight was chosen empirically in preliminary experiments. Lane-changes of surrounding vehicles can be detected by a change of lane index in two consecutive time steps. To ensure the same number of vehicles in two successive states of a transition, during training, dummy vehicles are added in case they only appear in one of the states because they leave or enter sensor range. This is necessary for the calculation of the Q-values with the permutation equivariant network architecture. In the execution phase this is not relevant.

A. Comparative Analysis

We compare Deep Surrogate-Q to the rule-based controller of SUMO with lane change model LC2013 and to the state-of-the-art DeepSet-Q algorithm. Since it has already been shown that a Deep Set representation is outperforming other methods using input representations such as fully-connected, recurrent or convolutional neural network modules for this specific application at hand, we omit to include these other baselines in this work and refer to [6] for an extensive comparison. In DeepSet-Q, the features of all surrounding vehicles are projected to a latent space by the network module $\phi$ in a similar manner as in Surrogate-Q. The combined representation of all surrounding vehicles is computed by $\Psi(s_t|x_t^\text{agent}) = \rho \left( \sum_{x \in s_t} x_{\text{agent}} \phi(x) \right)$. Static features describing the agents state $x^\text{agent}$ are fed directly to the Q-module, and the Q-values are computed by $Q_{\text{DS}} = Q(\Psi(s_t|x_t^\text{agent})|x_t^\text{agent}, a)$, where $||$ denotes a concatenation of two vectors and $a$ is the action of the agent. The updates are performed for every transition $i$ in a minibatch of size $m$ with $y_i = r_i + \gamma \max_a Q'(\Psi(s_{i+1}|x_{i+1}^\text{agent})||x_{i+1}^\text{agent}, a)$ using a slowly updated target network $Q'$. To update parameters we perform a gradient step on the loss $\frac{1}{m} \sum_i (Q_{\text{DS}}(s_t, a_t) - y_i)^2$. If not denoted differently, every network is trained with a batch size of 64 for $2.5 \cdot 10^6$ gradient steps and optimized by Adam [19] using a learning rate of $10^{-4}$. Rectified Linear Units (ReLU) are used as activation function in all hidden layers of all architectures. We update target networks by Polyak averaging. To prevent the predictions from overestimation, we further apply Clipped Double-Q learning [20]. Target networks are updated with a step-size of $\tau = 10^{-4}$. The architectures were optimized using Random Search with the settings shown in [6]. The neural network architectures are shown in Table I.

B. Simulation

We use the open-source SUMO traffic simulator [21] and perform experiments on a 1000m circular highway with three lanes, with the same settings as proposed in [6]. To create a realistic traffic flow, vehicles with different driving behaviors are randomly positioned across the highway. The
behaviors were varied by changing the SUMO parameters maxSpeed, lcSpeedGain and lcCooperative. For training, all datasets were collected on scenarios with a random number of 30 to 90 vehicles. Agents are evaluated for every training run on different scenarios to smooth out the high variance in the stochastic and unpredictable highway environment. The number of vehicles varies from 30 to 90 cars, and for each fixed number of vehicles, 20 scenarios with different a priori positions. We use all tracks with 3 lanes. Additionally, we trained on transitions extracted from the open-source HighD traffic dataset [10]. The dataset consists of 61 top-down recordings of German highways, resulting in a total of 147 driving hours. The recordings are preprocessed and contain lists of vehicle ids, velocities, lane ids and positions. We use all tracks with 3 lanes. Additionally, we filter a time span of 5 s before and after all lane changes in the dataset with a step size of 2 s, leading to a consecutive chain of 5 time steps and in total a replay buffer of \( \sim 18,000 \) transitions with \( \sim 4000 \) lane changes. A visualization of the dataset is shown in Figure 2 (left).

### C. Real Data

Additionally, we trained on transitions extracted from the open-source HighD traffic dataset [10]. The dataset consists of 61 top-down recordings of German highways, resulting in a total of 147 driving hours. The recordings are preprocessed and contain lists of vehicle ids, velocities, lane ids and positions. We use all tracks with 3 lanes. Additionally, we filter a time span of 5 s before and after all lane changes in the dataset with a step size of 2 s, leading to a consecutive chain of 5 time steps and in total a replay buffer of \( \sim 18,000 \) transitions with \( \sim 4000 \) lane changes. A visualization of the dataset is shown in Figure 2 (left).

### VI. RESULTS

First, we studied the required driving time to collect a certain number of lane-changes, considering transitions from test-drivers performing 5% and 20% lane-changes and transitions collected from all drivers in sensor-range. Figure 3 shows the cumulative sum of lane-changes for the two test drivers and the total sum of lane-changes of all surrounding vehicles in the 1 km highway scenario as proposed in [6], with 30 up to 90 vehicles per scenario and with 12 surrounding vehicles around the agent on average. A test driver performing as many lane-changes as possible (20% lane-changes) is compared to a more realistic driver model\(^1\) performing only 5% lane-changes. The latter requires a much higher amount of driving hours in order to collect the same amount of lane-changes.

We compared the Surrogate-Q agent with a DeepSet-Q agent in the same highway scenario in SUMO. Results are shown in Figure 4a. As additional measure of performance, we choose the sum of mean return over all scenarios and provide significance tests using Welch’s t-test. For a large amount of 500,000 transitions (\( \sim 280 \) driving hours) collected by a driver with 5% lane-changes, Surrogate-Q is outperforming Deepset-Q with a p-value of \( < 0.001 \). Decreasing the amount of transitions by \( 1/10 \) leads to a high decrease of performance for DeepSet-Q. For 50,000 transitions (\( \sim 28 \) driving hours), DeepSet-Q shows significantly lower performance than Surrogate-Q with a p-value of \( < 0.001 \). Additionally, Surrogate-Q is outperforming the rule-based controller for light traffic up to 60 vehicles (p-value \( < 0.01 \)) when trained on only 28 driving hours. Please note that differences between the approaches get smaller the more vehicles are on track because of maneuvering limitations in dense traffic. Surrogate-Q is even able to show similar performance without performing any lane-changes with the test vehicle at all, only by observing the transitions of other vehicles. This drastically simplifies data-collection, since such a transition set could be collected by setting up a camera on top of a bridge above a highway. The DeepSet-Q algorithm is not able to learn to perform lane-changes without the test vehicle itself performing lane-changes in the dataset. Thus, it learns to stay on its lane and achieves a much lower velocity than Surrogate-Q.

\(^1\) Driver model of the SUMO traffic simulation using the Krauss car following model in combination with LC2013 controller.

| TABLE I: Network architectures of DeepSet-Q and Surrogate-Q. FC(·) denote fully-connected layers. |
|-----------------------------------------------|
| DeepSet-Q | Surrogate-Q |
| Input(\( B \times \text{seq len} \times 3 \)) | Input(\( B \times \text{seq len} \times 6 \)) |
| \( \phi: \text{FC}(20), \text{FC}(80) \) | \( \phi: \text{FC}(20), \text{FC}(80) \) |
| \( \text{sum(·)} \) | \( \text{sum(·)} \) |
| \( \omega: \text{FC}(80), \text{FC}(20) \) | \( \omega: \text{FC}(80), \text{FC}(80) \) |
| \( \text{concat(·, Input(\( B \times 3 \))} \) | \( \forall x_j: \text{concat}(·, x_j) \) |
| \( Q: \text{FC}(100), \text{FC}(100) \) | \( Q: \text{FC}(80), \text{FC}(80) \) |
| Output(\( B \times 3 \)) | Output(\( B \times \text{seq len} \times 6 \)) |

fig:3 Cumulative sum of lane-changes per driving hours, for transitions collected by different driver models on a highway in the open-source traffic simulator SUMO [21].
The optimization of the action-value function for all vehicles in a scene virtually increases the batch size by augmenting the minibatch with one distinct imaginary transition for each of them. In order to evaluate the added value of updating w.r.t. different positions in the same scene in parallel, we compare our approach to a DeepSet-Q agent with an analogously increased replay buffer and batch size, but with an underlying uniform sampling distribution. This results in an agent updated with the same number of samples per minibatch, with the only difference being the sampling distribution. Since there is a variable batch size depending on the number of vehicles in Surrogate-Q, we multiply the default batch size by 12 which corresponds to the average number of surrounding cars. The results of the adaption of the batch-size for DeepSet-Q in order to achieve the same number of updates per minibatch than in Surrogate-Q is shown in Figure 4b for a transition set of size 100,000. Both approaches are trained for the same number of 1.25 · 10^6 gradient steps\(^2\). Surrogate-Q is outperforming the uniform sampling technique with a small batch-size of 5 · 12, showing a p-value of < 0.05 and with a large batch-size of 64 · 12 with a p-value of < 0.001. A higher batch size, which leads to the same amount of updates per batch as for Surrogate-Q, shows a significant performance decrease. This emphasizes the advantage of the replay sampling in Surrogate Q-learning. Our findings suggest that Surrogate Q-learning via a permutation equivariant architecture leads to a more consistent gradient, since the TD-errors are normalized w.r.t. all predictions for the different positions in the scene while keeping the i.i.d. assumption of stochastic gradient descent by sampling uniformly from the replay buffer. Besides, Surrogate Q-learning offers the possibility to evaluate several actions at once because all vehicles are represented by the same features and all execute the same actions. The evaluation of multiple actions simply leads to the agent having access to more knowledge (w.r.t. one specific state) in shorter time, which is an advantage compared to DeepSet-Q. Additionally, the training of the permutation equivariant architecture is tremendously more efficient. The training of DeepSet-Q with a batch size of 768 takes 6 days, the training of Surrogate-Q only 12 hours on a Titan Black GPU for the same amount of updates. The performance of the agent trained on the real dataset consisting of approximately 18,000 transitions is shown in Figure 4c. Despite mismatches between simulation and the real recordings, Surrogate-Q trained on HighD shows a comparable performance to the agent trained on 50,000 transitions in simulation when evaluated in SUMO.

VII. CONCLUSION

We introduced a novel deep reinforcement learning algorithm, which can efficiently be implemented via a flexible permutation equivariant neural network architecture. Exploiting off-policy learning, the algorithm takes transitions of all vehicles in sensor range into account by considering a global reward function. Surrogate-Q is extremely efficient in terms of the required number of transitions and with respect to training runtime. Due to the novel architecture of the Q-network, the agent can efficiently exploit all useful information in a given transition set, which alleviates the problem of data collection with a test vehicle significantly. Data can be collected by recordings from top-down views of highways (e.g. from bridges or drones), which simplifies the pipeline in training autonomous vehicles tremendously. Additionally, we successfully showed that Surrogate-Q can be trained on real data.

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