Using Counterfactual Reasoning and Reinforcement Learning for Decision-Making in Autonomous Driving

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Abstract—In decision-making for autonomous vehicles, we need to predict other vehicle’s behaviors or learn their behavior implicitly using machine learning. However, often the predictions and learned models have errors or might be wrong altogether which can lead to dangerous situations. Therefore, decision-making algorithms should consider counterfactual reasoning such as: what would happen if the other agents will behave in a certain way? The approach we present in this paper is two-fold: First, during training, we randomly select behavior models from a behavior model pool and assign them to the other vehicles in the scenario, such as more passive or aggressive behavior models. Second, during the application, we derive several virtual worlds from the actual world that have the same initial state. In each of these worlds, we also assign behavior models from the behavior model pool to others. We then evolve these virtual worlds for a defined time-horizon. This enables us to apply counterfactual reasoning by asking what would happen if the actual world evolves as in the virtual world. In uncertain environments, this makes it possible to generate more probable risk estimates and, thus, to enable safer decision-making. We conduct studies using a lane-change scenario that shows the advantages of counterfactual reasoning using learned policies and virtual worlds to estimate their risk and performance.

I. INTRODUCTION

Decision-making for autonomous vehicles poses a challenging task due to the uncertainties in real-world traffic scenarios. The behavior of other traffic participants is at best partially observable and, thus, requires decision-making algorithms that can cope with uncertainties. Deterministic policies can only yield optimal solutions given full observability \cite{1}. In uncertain environments, stochastic policies can even lead to increased robustness \cite{2}.

Part of the uncertainty in traffic scenarios stems from the unknown behaviors and intentions of other traffic participants. As the behavior models of traffic participants are not known and are at best only partially observable, assumptions about these have to be made. So naturally, questions like ‘What would happen if the other vehicles will behave in a certain way?’ arise in the context of decision-making. Algorithms that do consider such questions in their reasoning process are considered as counterfactual decision-making algorithms. By using counterfactual reasoning, our approach can better assess the overall risk and performance of executing a learned policy in a given scenario.

We use deep Reinforcement Learning (RL) to learn a stochastic policy in such uncertain environments. Unlike conventional decision-making algorithms, RL does not require predicting other traffic participants but it learns from collected experiences. However, the behavior of other traffic participants still has to be defined before an episode, which also introduces assumptions about the other’s behaviors. Even methods like safe-reinforcement learning fail to achieve sufficient results if the behavior of others is unexpected.

The approach we present in this work is two-fold. First, during training, we separate the training and application phase. Second, by using so-called virtual worlds during the application phase, we increase the robustness and safety of executing the learned policy.

During training, we assign behaviors sampled from a behavior model pool to the other traffic participants. Due to this, the ego vehicle can not be certain about how the others will behave in a scenario. After training has conceded, the learned policy performs already well in most of the scenarios. However, as still some collisions persist, the learned policy would not be directly applicable in safety-critical applications. Therefore, as above-motivated, we use virtual worlds and counterfactual reasoning to assess the risk and performance of the learned RL policy in a scenario.

During application, we clone the current world and derive several virtual worlds having the same initial state – each vehicle having the same initial state as in the actual world. In each of these virtual worlds, we assign behaviors by sampling these from a behavior model pool as during training. These virtual worlds are then forward-simulated for a pre-defined horizon. By using these virtual worlds it can be assessed how well the learned RL policy would perform if the vehicles behave as defined in the virtual world. It raises the question:
‘How well would the learned policy perform if the other vehicles will behave as in the virtual world?’ For example, one virtual world can have passive behaviors and another one can have more aggressive ones. As there is only one true behavior of the other vehicles, this can be seen as counterfactual reasoning as we assume nonfactual behaviors for the other vehicles. By including all of these different, counterfactual behaviors in the decision-making process, the overall risk and performance of the learned RL policy can be better estimated for scenarios that have never been seen during training. If the risk is too high or does not perform well, the learned policy is not executed and the ego vehicle instead stays on its lane.

To sum up, our novel approach combines counterfactual reasoning with reinforcement learning to cope with the behavioral uncertainties of other traffic participants. Due to using virtual worlds and counterfactual reasoning we can estimate better what would happen if the others behaved differently than expected. Using a lane-change scenario we show that the novel approach can lower the collision-rate to zero, which is important in safety-critical applications. We conduct studies on varying the number of virtual worlds and the maximum allowed collision-rate and the minimum allowed success-rate in these.

Our paper is further structured as follows: Section II gives an overview of reinforcement learning and counterfactual decision-making. Section III outlines the proposed approach and Section IV presents results and discusses findings.

II. RELATED WORK

In this section, we outline state-of-the-art reinforcement learning and provide an overview of counterfactual decision-making.

Reinforcement Learning (RL) collects experiences in an environment and tries to maximize its future expected cumulative reward. This has especially advantages when the models in the environment are not or only partially known. RL achieves state-of-the-art performance in a variety of tasks [3–5]. Although RL can be subdivided into policy- and value-based methods, a combination of both in the form of Actor Critic methods has empirically shown to work well. The Proximal Policy Optimization (PPO) uses an actor network that has a bounded surrogate objective function [6]. The PPO has a similar concept as using Trust Region Policy Optimization (TRPO) [7] but is computationally less expensive. Two of the more recent AC methods include the Soft Actor Critic (SAC) and Maximum a Posteriori Policy Optimization (MPO) [8, 9]. Both of these approaches achieve state-of-the-art results in continuous control tasks. Hart et al. [10] applied the SAC method in a lane-merging scenario. They additionally use a post-optimization to lower the remaining collisions and to improve the ride comfort. Shalev-Shwartz et al. [11] use RL to find long-term driving strategies. They use an option graph for higher-level strategy planning. However, the above-stated approaches assume each traffic participant having a given and constant behavior. In real-world traffic, the behaviors of others are unknown and can at best only be partially observed. In our approach, we vary the behavior models of the others during training and during application, we utilize virtual worlds. We use these virtual worlds to perform counterfactual reasoning with the learned RL policy. Therefore, we do not only consider one world as the true world but consider many.

In the field of game theory, counterfactual reasoning deals with the rational deliberation of multiple agents. It can mainly be divided into two main categories: casual and epistemic counterfactual reasoning. In causal counterfactual reasoning, the agents reason about what would happen if they or the other agents act in ways they know or believe to be nonactual [12]. As in Section IV explained, sampling behaviors from a model pool for other traffic participants can be seen as assigning nonactual behaviors to other traffic participants. This is since that each traffic participant only can have one true behavior. Pearl and Mackenzie [13] describe the human capacity to reason about counterfactual outcomes of past experience with the goal of mining worlds that could have been. Contrary to this, we do not mine past worlds but predict worlds into the future and evaluate these. Therefore, we ask questions like: What would happen if the world will evolve in a certain way? Buesing et al. [14] propose a counterfactual guided-policy search reinforcement learning algorithm. In their work, they leverage a model to consider alternative outcomes and, thus, increase the algorithms sample efficiency on required experiences. Counterfactual reasoning also has been applied in the field of autonomous driving [15]. In their work, they consider counterfactual behaviors in the prediction using an intention tree search.

In our approach, we combine counterfactual reasoning with state-of-the-art reinforcement learning. By using counterfactual virtual worlds, we can better estimate the risk of executing a learned policy in a given situation. Additionally, we can evaluate the performance of the policy with respect to many aspects of the virtual worlds.

III. APPROACH

In this section, we describe the Reinforcement Learning (RL) approach and how we apply it in a semantic simulation.

We use RL to learn a policy $\pi(a|s) = a$ for the ego vehicle that maximizes its future expected cumulative reward. We use a semantic simulation framework with $N$ other vehicles that are represented by an object-list. Each of the other traffic participants has a behavior model $B$ that defines how it behaves within the simulation. A behavior model pool $\mathcal{M}$ that contains sampled behavior models, such as passive models $B_{\text{passive}}$ or more aggressive models $B_{\text{aggressive}}$ is used.

The Soft Actor Critic (SAC) reinforcement learning method to learn a policy $\pi(a|s)$ for the ego vehicle is used [8]. The SAC algorithm does not only maximize the future expected cumulative reward but also the entropy. As shown in their work, this leads to exploring several goals instead of just choosing one greedily. We use a ‘ClosestAgentObserver’
that transforms the semantic environment into a vectorial representation $q$ that is compatible with deep neural networks. The ‘ClosestAgentObserver’ concatenates the states of the $n$-nearest vehicles into a single vector. Additionally, we also use an ‘Evaluator’ that calculates the reward and checks whether an episode is terminal. The reward function of the ‘Evaluator’ is designed to provide a high level of comfort and safety. It can be mathematically denoted as

$$r(s,a) = r_{\text{comfort}}(s,a) + r_{\text{safety}}(s,a) + r_{\text{goal}}(s,a). \quad (1)$$

with the three terms in Equation (1) defined as follows:

- $r_{\text{comfort}}$ determines the comfort by penalizing deviations to the desired velocity as well as high input values,
- $r_{\text{safety}}$ penalizes leaving the drivable area and collisions with other vehicles,
- and $r_{\text{goal}}$ provides a guiding reward to reach the goal and also rewards reaching the final goal.

As we use a single-track model for the ego vehicle, the inputs are the steering-rate $\delta$ and the acceleration $a$. The terms in Equation (1) are additionally weighted in favor of providing a high level of safety. The ‘Evaluator’ terminates an episode, once a collision of the ego-agent occurred, the goal has been reached or the drivable area has been left. Based on the collected observations $o$, the actions taken by the policy $\pi(a|s) = a$ and the rewards $r$, the SAC algorithm is then able to improve its policy.

A. Training Process

During training, we uniformly sample behavior models from the behavior model pool $M$ and assign these models to the other traffic participants. The ego vehicle acts according to the learned policy $\pi(a|s)$. The risk-rate $\rho(\pi(a|s),w^*)$ is defined as the average collision rate over all the virtual worlds $w^*$. This can be mathematically denoted as

$$\rho(\pi(a|s),w^*) = \frac{1}{L} \sum_i \text{Collision}(w_i). \quad (2)$$

If in Equation (2) collisions occur in each virtual world, the risk $\rho(\pi(a|s),w^*)$ would be 100%. However, the risk-rate $\rho(\pi(a|s),w^*)$ alone is not sufficient to determine whether the policy should be executed in the actual world the ego vehicle is in. Another important criterion is how often the

ego vehicle acts in the world $w_P$ and collects experiences which it then improves its policy $\pi(a|s)$. The architecture, parameters, and results of the training process are provided in Section [IV].

B. Counterfactual Reasoning

After the training has conceded, we now have a policy $\pi(a|s)$ that already achieves a very good performance as shown in [IV]. However, collisions persist which makes the learned policy $\pi(a|s)$ not directly applicable in safety-critical applications, such as autonomous driving.

In this work, we use causal counterfactual reasoning where we assume nonfactual behavior for the other vehicles using virtual worlds. These virtual worlds are derived from the actual world $w$ the ego vehicle is in. All virtual world have initially the same state, but evolve differently over time. This is due to the fact, that in each of these virtual worlds the behavior models are randomly sampled from the behavior model pool $M$. To better reason what would happen if the others will behave in a certain way, we create $L$ virtual worlds $w^*_i$. In Section [IV] we show the effect of varying the number $L$.

We then simulate all virtual worlds into the future for a pre-defined time-horizon $T$. The ego vehicle acts in each of these virtual worlds using its learned RL policy $\pi(a|s)$. By doing this, we can estimate how well the learned policy $\pi(a|s)$ copes in the virtual worlds $w^* = [w^*_1,\ldots,w^*_L]$. Therefore, we now can answer the question: How would the learned policy $\pi(a|s)$ perform if the world evolves like in the virtual world? This introduces counterfactual reasoning in the application of the RL policy. For example, we can reason counterfactually about what would happen if all the other agents will behave passively or aggressively.

As the intent and the true behavior model of other traffic participants is not observable, we cannot reason which of the virtual world will be the closest to the actual world. However, it lets us conduct studies on a wide range of possible future worlds and e.g. if the policy performed well in most of them and if collisions occurred in these. We, therefore, can assess the risk and performance better and how successful executing the learned policy in the current world would be.

C. Risk and Performance

To determine whether the learned policy $\pi(a|s)$ should be executed in the current situation, we define several measures.

The risk-rate $\rho(\pi(a|s),w^*)$ is defined as the average collision rate over all the virtual worlds $w^*$. This can be mathematically denoted as

$$\rho(\pi(a|s),w^*) = \frac{1}{L} \sum_i \text{Collision}(w_i). \quad (2)$$

If in Equation (2) collisions occur in each virtual world, the risk $\rho(\pi(a|s),w^*)$ would be 100%. However, the risk-rate $\rho(\pi(a|s),w^*)$ alone is not sufficient to determine whether the policy should be executed in the actual world the ego vehicle is in.
learned policy reaches the defined goal. Therefore, we define a success-rate $\xi(\pi(a|s), w^*)$ similar to Equation (2) as

$$\xi(\pi(a|s), w^*) = \frac{1}{L} \sum_i \text{Success}(w_i). \tag{3}$$

By combining the above-stated risk-rate $\rho(\pi(a|s), w^*)$ and the success-rate $\xi(\pi(a|s), w^*)$, we can now define a strategy when the learned policy should be executed. On one hand, the policy has to provide a high level of safety even with larger deviations of the other vehicle’s assumed behavior models. On the other hand, the learned policy has to reach the goal sufficiently often enough with these deviations persistent. As autonomous driving is a safety-critical application, we need a collision-rate $\rho(\pi(a|s), w^*)$ close to zero or zero. The success-rate $\xi(\pi(a|s), w^*)$ does not adhere to such high standards, as it is not directly imposing dangers to the ego vehicle.

We introduce a logic and thresholds that define when it is safe and beneficial enough to execute the learned policy in a given world $w_p$ using the virtual worlds $w^*$. The pseudo-code formulation on whether a policy $\pi(a|s)$ should be executed in a scenario can be written as

\begin{align*}
\text{Execute} & \quad \pi(a|s) \\
\text{subject to} & \quad \xi(\pi(a|s), w^*) & \geq & \xi_{\text{min,success}} \tag{4a} \\
& \quad \rho(\pi(a|s), w^*) & \leq & \rho_{\text{max,collision}} \tag{4b} \\
& & & \tag{4c}
\end{align*}

with $\xi_{\text{min,success}}$ being the minimum required success-rate and $\rho_{\text{max,collision}}$ the maximum collision-rate over all virtual worlds $w^*$. We evaluate choosing the thresholds $\xi_{\text{min,success}}$ and $\rho_{\text{max,collision}}$ in Section IV in greater detail.

If Equation (3) is not fulfilled due to a high $\rho$ and low $\xi$ in the virtual worlds $w^*$, the learned RL policy is not executed in the actual world $w$. In this case, we assign the Intelligent Driver Model (IDM) [16] to the ego vehicle and the ego vehicle stays on the current lane it is on. By definition, this leads to collision-free scenarios and, thus, we count these as such. However, by not executing the learned RL policy, the ego vehicle also will not reach its defined goal. In IV we provided detailed results of the novel approach and how to choose the thresholds $\rho_{\text{max,collision}}$ and $\xi_{\text{min,success}}$.

IV. EXPERIMENTS

In this work, we use the semantic simulation framework BARK and its machine learning extension BARK-ML for interactive behavior planning. To demonstrate the novel approach, we chose a lane-change scenario with the ego vehicle having the intent of merging onto the left lane. The ego vehicle uses a single-track model as defined in [17]. All vehicle’s positions are uniformly sampled on the left and right lane. A vehicle on the right lane is then picked and defined as the ego vehicle.

The other vehicles in the scenario behave according to the Intelligent Driver Model (IDM) [16]. The initial velocity of all vehicles is sampled within a range of $[10m/s, 15m/s]$

[https://github.com/bark-simulator/bark/](https://github.com/bark-simulator/bark/)

[https://github.com/bark-simulator/bark-ml/](https://github.com/bark-simulator/bark-ml/)

and the desired velocity for all vehicles – including the ego vehicle – is set to $v_{des} = 15m/s$. We create a behavior model pool $\mathcal{M}$ having sampled behavior models that is used during training and application. To generate this behavior model pool $\mathcal{M}$, we sample the IDM desired time headway parameter $T_{head}$ uniformly in a range of $[1, 5]$. As $T_{head}$ is responsible for the gap keeping distance, more passive and aggressive driving styles are modeled. The complete parametrization of the IDM is given by:

"BehaviorIDM": {
    "MaxVelocity": 30.0,
    "MinimumSpacing": 2.0,
    "DesiredTimeHeadway": [1.0, 5.0],
    "MaxAcceleration": 2.5,
    "DesiredVelocity": 15.0,
    "ComfortableBrakingAcceleration": 1.6,
    "MinVelocity": 0.0,
    "Exponent": 4
}

Furthermore, BARK-ML is an episodic simulation, where an ‘Evaluator’ determines when an episode is terminal. In this work, an episode is counted as terminal if the maximum number of steps has been reached, a collision with the ego vehicle occurred or the ego vehicle has reached its goal. We set the maximum number of steps is limited to 60. For the goal, we define a polygonal area on the left lane with additional state limits on the speed $v$ and vehicle angle $\theta$. The vehicle angle $\theta$ is allowed to have deviations of $\pm 0.08$ of a defined target vehicle angle $\theta_{target}$. For the speed, we set a goal range of $[10m/s, 16m/s]$ that is allowed for the goal to be reached.
We train the agent for 300 episodes, after which a collision-rate $\rho_{\text{max}}$ of the actual world is larger than 0.25. However, choosing the thresholds for $\rho$ and $\xi$ is nontrivial as this could lead to too passive or risky behaviors.

Figure 5 shows the collision-rate $\rho_{\text{actual}}$ of the actual world plotted over the maximum collision-rate $\rho_{\text{max}}$ of the virtual worlds. Once the collision-rate $\rho$ is larger than $\rho_{\text{max}}$ in the virtual worlds $w^*$, the policy is not executed in the actual world. It can be seen, that the higher $\rho_{\text{max}}$ is the higher the success-rate $\xi_{\text{actual}}$ becomes as the policy is being executed also more often. However, this also causes an increasing collision-rate $\rho_{\text{actual}}$. Larger increases in risk should be disregarded in favor of safety in safety-critical applications, such as autonomous driving.

Figure 5 shows four virtual worlds at time $T = 4s$ that all initially had the same state but evolved differently over time due to different sets of behavior models. As can be seen, in the scenario on the left a collision occurs. In the other virtual worlds, the learned policy does not cause a collision and reaches the ego vehicle’s goal. Using these four virtual worlds the collision-rate would be $\rho = 0.25$. However, choosing the thresholds for $\rho$ and $\xi$ is nontrivial as this could lead to too passive or risky behaviors.

Figure 3 shows four virtual worlds at time $T = 4s$ that all initially had the same state but evolved differently over time due to different sets of behavior models. As can be seen, in the scenario on the left a collision occurs. In the other virtual worlds, the learned policy does not cause a collision and reaches the ego vehicle’s goal. Using these four virtual worlds the collision-rate would be $\rho = 0.25$. However, choosing the thresholds for $\rho$ and $\xi$ is nontrivial as this could lead to too passive or risky behaviors.

Figure 4 shows the success-rate $\xi_{\text{actual}}$ of the actual world plotted over the maximum collision-rate $\rho_{\text{max}}$ of the virtual worlds. Once the collision-rate $\rho$ is larger than $\rho_{\text{max}}$ in the virtual worlds $w^*$, the policy is not executed in the actual world. It can be seen, that the higher $\rho_{\text{max}}$ is the higher the success-rate $\xi_{\text{actual}}$ becomes as the policy is being executed also more often. However, this also causes an increasing collision-rate $\rho_{\text{actual}}$. Larger increases in risk should be disregarded in favor of safety in safety-critical applications, such as autonomous driving.

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worlds before executing the policy in the actual world, the risk and success of executing the learned policy can be better estimated. Therefore, the applicability of learned RL policies in safety-critical applications is increased by our proposed method. This is of course if one leaves aside the concerns and restrictions that come with neural networks in safety-critical applications. Using table-based approaches instead of deep neural networks or post-processing of the RL solution [10] could mitigate these restrictions.

V. Conclusion

In this work, we presented an approach combining reinforcement learning with counterfactual reasoning. Using reinforcement learning, we learn a policy in scenarios with the other traffic participants having varying behavior models. Thus, it learns to cope with a wide range of behavior models – ranging from passive to more aggressive ones. However, after the training has conceded the learned policy will still cause collisions in some scenarios. In this work, we introduce virtual worlds in which the learned policy is evaluated before executing it in the actual world. Each virtual world is a clone of the actual world but different behavior models are assigned to the other vehicles. The ego vehicle then acts in these using its learned policy. We evolve the virtual worlds until their terminal state has been reached. By additionally introducing risk and performance measures, we are then able to decide whether the policy is safe and performant enough to be executed in the actual world. Our new approach enables to achieve a collision-rate of zero percent which is crucial in safety-critical applications, such as autonomous driving.

Future work could include how similar a virtual world is to the actual world using e.g. probabilistic inference. Thus, higher importance could be assigned to virtual worlds that are closer to the actual world.

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