Improving Reward Estimation in Goal-Conditioned Imitation Learning with Counterfactual Data and Structural Causal Models

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Abstract: Imitation learning has emerged as a pragmatic alternative to reinforcement learning for teaching agents to execute specific tasks, mitigating the complexity associated with reward engineering. However, the deployment of imitation learning in real-world scenarios is hampered by numerous challenges. Often, the scarcity and expense of demonstration data hinder the effectiveness of imitation learning algorithms. In this paper, we present a novel approach to enhance the sample efficiency of goal-conditioned imitation learning. Leveraging the principles of causality, we harness structural causal models as a formalism to generate counterfactual data. These counterfactual instances are used as additional training data, effectively improving the learning process. By incorporating causal insights, our method demonstrates its ability to improve imitation learning efficiency by capitalizing on generated counterfactual data. Through experiments on simulated robotic manipulation tasks, such as pushing, moving, and sliding objects, we showcase how our approach allows for the learning of better reward functions resulting in improved performance with a limited number of demonstrations, paving the way for a more practical and effective implementation of imitation learning in real-world scenarios.

1 INTRODUCTION

The pursuit of training autonomous agents to perform tasks efficiently and effectively remains a fundamental challenge. While reinforcement learning has made significant strides (Sutton and Barto, 2018), it is often plagued by the reliance on reward engineering, making it impractical for real-world applications. One promising alternative is imitation learning, a paradigm that offers notable advantages over reinforcement learning, as it alleviates the arduous task of reward engineering and improves data efficiency by reducing the need for extensive trial and error.

Despite its promise, however, imitation learning is not without limitations. Acquiring expert demonstrations can be a prohibitively expensive and resource-intensive process, cumbersome or even unfeasible. In turn, the reliance on a limited number of demonstrations often leads to suboptimal performance or results in catastrophic failures when the training data is not sufficiently representative of the task's complexity.

In recent years, there has been a growing recognition of the role of causality in improving learning-based approaches (Schölkopf, 2019) (Kaddour et al., 2022). Causality, the study of cause-and-effect relationships, has emerged as a powerful tool for gaining a deeper understanding of how agents interact with their environments. It provides a framework for reasoning about the consequences of different actions and interventions, which offers the potential to enhance the robustness and efficiency of learning.

This work presents a novel causal approach to improve the learning of policies from limited demonstrations in goal-conditioned settings, leveraging causality by learning Structural Causal Models (SCMs) that represent the expert's behavior within its environment. We harness the learned SCM to generate counterfactual data that simulate what would have happened had the expert pursued different goals. The counterfactual data serves as supplementary training data for goal-conditioned imitation learning, allowing agents to learn more effectively with less data.

The key contributions of this work include **1)** formulating a methodology to learn the SCM of high-level expert-environment interactions (section 3.2.1), **2)** using SCM to generate counterfactual data that

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correspond to alternative goals and actions (section 3.2.2), and **3)** demonstrating how the counterfactual data could serve as additional training data to improve learning (section 4.2). We evaluate our method in a series of simulated robotic manipulation tasks consisting of pushing, moving and sliding objects with a 7-DoF robotic arm. Experiments demonstrate that our method is able to improve goal-conditioned, generative adversarial imitation learning, especially when few demonstrations are available. The obtained results shed light on the potential of causality to address fundamental challenges in imitation learning and to advance the capabilities of autonomous agents in learning complex tasks.

2 BACKGROUND

2.1 Imitation Learning

Imitation learning enables agents to acquire skills by imitating expert behavior rather than relying on trial and error. Several key approaches have emerged in imitation learning. Behavior cloning involves learning a policy that mimics the actions of an expert based on observed state-action pairs (Bain and Sammut, 1999). Inverse reinforcement learning (Russell, 1998) (Mnih et al., 2013) (Silver et al., 2016) aims to recover the underlying reward function from expert demonstrations, allowing agents to generalize beyond specific trajectories. Generative Adversarial Imitation Learning (GAIL) (Ho and Ermon, 2016) bypasses this intermediate step and directly learns the policy from demonstrations by formulating imitation learning as a two-player minimax game between a discriminator D and the policy π. The discriminator aims to distinguish between expert trajectories and agent-generated trajectories, while the policy generator seeks to produce trajectories that are indistinguishable from expert data.

Goal-Conditioned Imitation Learning. In goal-conditioned imitation learning (Liu et al., 2022), each task or trajectory is uniquely characterized by a distinct goal state. Thus, the policy is conditioned on both the observed states and designated goals, namely, as $\pi : \mathcal{S} \times \mathcal{G} \rightarrow \mathcal{A}$.

One common challenge in goal-conditioned settings is sparse rewards (Hare, 2019), typically taking on a binary form that denotes goal attainment. This poses a substantial challenge for traditional reinforcement learning (RL) methods due to the absence of informative reward signals in unsuccessful trajectories. Hindsight Experience Replay (HER) (Andrychowicz et al., 2017) offers a remedy to this problem by introducing a relabeling trick that reinterprets unsuccessful trajectories as valuable learning experience. By treating these trajectories as successful ones with different goal states, *i.e.* states that were actually achieved, the policy is able to learn from its failures which drastically improves sample efficiency in RL.

GoalGAIL (Ding et al., 2019) combines GAIL with HER relabeling strategy, which yields notable improvements in learning efficiency and makes it a compelling approach for goal-conditioned imitation learning. Our proposed approach extends GoalGAIL by leveraging counterfactual data to improve reward learning efficiency.

2.2 Structural Causal Models (SCMs)

Structural Causal Models (SCMs) (Pearl et al., 2000) offer a formal framework for modeling causal relationships in a system. At the core of SCMs lie two fundamental types of variables: endogenous and exogenous. Exogenous variables represent uncontrollable external factors and serve as independent sources of variation. Endogenous variables, on the other hand, represent outcomes influenced by other variables within the model through structural equations, capturing the system's internal dynamics. These equations usually take the following form:

$$X_i = f_i(Parents(X_i), U_i) \quad (1)$$

where X_i and U_i denote endogenous and exogenous variables respectively, f_i is a deterministic function specifying the causal dependencies between the variables, and $Parents(X)$ denotes the variables that have a direct causal effect on X. An SCM is typically associated with a Directed Acyclic Graph (DAG) as a graphical representation of the causal system, where the nodes correspond to variables, and the directed edges indicate causal dependencies.

2.3 Counterfactual Reasoning with SCMs

Structural Causal Models (SCMs) offer a formal framework for conducting counterfactual reasoning (Pearl, 2013). The process of counterfactual reasoning with SCMs involves three essential steps.

- **Abduction:** This step consists in recovering the values of exogenous variables within the SCM based on the observed evidence.
- **Intervention:** Once exogenous variables are inferred, we modify the SCM by intervening on one or more variables of interest. This represents a

hypothetical change to the system, allowing to explore "what if" scenarios.

- **Prediction:** We can predict the counterfactual outcome of interest using the updated structural equations within the modified SCM.

3 CAUSAL MECHANISM AND COUNTERFACTUAL REASONING

3.1 Problem Formulation

In this work, we consider a goal-conditioned Markov Decision Process (MDP) defined by a tuple $(\mathcal{S}, \mathcal{G}, \mathcal{A}, P, R, \gamma)$, where $\mathcal{S}$ denotes the state space, $\mathcal{A}$ the action space, $\mathcal{G} \subset \mathcal{S}$ the goal space, $P(s_{t+1}|s_t, a_t)$ the transition dynamics, $R(s_t, a_t, g_t)$ the true reward function indicating whether the goal was achieved and $0 < \gamma < 1$ the discount factor.

Given a set of N expert trajectories $\mathcal{D}_E = \{(s_t^i, a_t^i, g^i), 0 \leqslant t \leqslant T\}_{1 \leqslant i \leqslant N}$, our goal is to learn a policy π that matches the distribution of the trajectories in the demonstrations by optimizing the following objective:

$$\min_D \max_\pi \mathbb{E}_\pi [\log D(s,g,a)] + \mathbb{E}_{\pi_E} [\log(1 - D(s,g,a))] \tag{2}$$

where π_E denotes the expert policy and D a discriminator that outputs a score for each tuple (s,g,a).

In goal-conditioned settings, the policy is typically conditioned on the current state and the goal. In this work, we make the choice of introducing a latent variable denoted m_t, which we refer to as the *motivator*. m_t is causally affected by both s_t and g and represents the intermediate relative goal at state s_t in relation to achieving the absolute goal g.

From a causal perspective, the concept of intermediate relative goal is more informative to the agent. The policy is therefore conditioned on m_t instead of (s_t, g_t). One could argue that m would naturally correspond to the intermediate features learned by a neural policy. However, this is not the case in our formulation. To understand this, let us start by depicting the SCM that we assume and its corresponding causal graph.

We assume that our SCM satisfies the following structural equation, as shown in the causal graph in Figure 1:

$$m_t = f_m(s_t, g, u_t) \tag{3}$$

where u_t denotes the exogenous variable capturing the external factors affecting the system as explained in section 2.2.

For simplicity, we omit time indexes for all variables in the remainder of this work, which should not introduce any ambiguity. Our goal is to learn the causal mechanism governing the generation of m, which corresponds to the above equation. Subsequently, we want to learn a policy conditioned on the motivator m. Details on how to learn the SCM and generate counterfactual data are provided in section 3.2 (section 4 describes how we leverage the learned SCM and the counterfactual data to learn the policy).

We therefore separate the processes of learning the structural equation of m and the policy π. Learning the former can be thought of as learning a high-level causal policy whose role is to generate abstract relative subgoals. The reason we choose to learn the causal model for a high-level policy is that it is simpler and easier than learning fine-grained causal relationships directly linking the state and goal pairs to actions, given a limited amount of expert data. To make an analogy, this can be thought of as learning the overall directions in a robot navigation problem instead of learning specific fine-grained actions such as controlling the forces applied by the robot actuators.

This results in two benefits. First, once the SCM is learned, one can reason counterfactually about what would have happened had the goal been different. This allows us to generate high-level counterfactual policy demonstrations in the form of (s,g,m). By conditioning the policy on counterfactual motivators, one can indirectly obtain counterfactual actions under a given policy. Second, by conditioning on m, we are separating policy training from the process of identifying relevant causal features. Neural networks are known for their tendency to learn spurious correlations rather than task-relevant features (Shah et al., 2020). By learning the causal mechanism of m and conditioning the policy on it, we are limiting the exposure of the policy to spurious features, as these will rather be captured by the exogenous variable u.

3.2 SCM Learning and Counterfactuals Generation

Given the SCM in equation (3), one could reason counterfactually for what would have been the action taken by the agent had its motivator been different. At a given timestep t, given an observed triplet (s,g,a), we want to predict the counterfactual motivator for an alternative goal $g\prime$ and infer the agent action given that motivator under the current policy.

Recall the three steps involved in the counterfactual reasoning process (see section 2.3). The first step consists of recovering the noise variable from

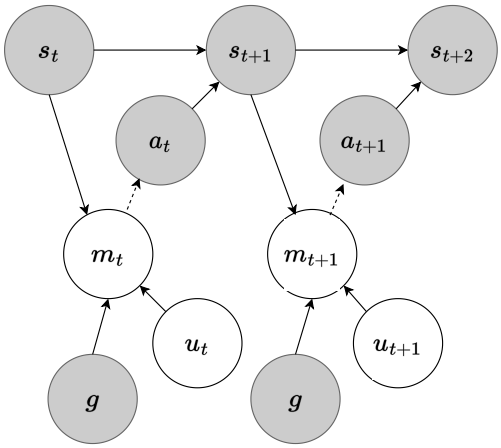


Figure 1: The causal graph describing the expert trajectories' generation process between t and $t+2$. Solid and dashed lines denote causal and conditional dependence, respectively. Shaded nodes are observed variables.

the observed evidence, which corresponds in our case to (s,g,a). Thus, we need to learn an inverse mapping from these observed variables to the independent noise term u which we assume follows a standard normal distribution. Similarly, to be able to perform the second and third steps, it is necessary to approximate the structural function f_m in equation (3). To capture the causal relationship between the variables, both functions need to be learned simultaneously so as to capture the joint distribution $p(m,u|s,g,a)$.

3.2.1 Learning the SCM

We cast the learning of both functions in a double Variational Autoencoder (VAE) (Kingma and Welling, 2013) setting, allowing us to approximate the two functions concurrently.

The encoders of the VAEs parameterize the mean and log-variance of two Gaussian distributions: $q^m(m|s,g,u) = \mathcal{N}(\mu_m(s,g,u), \sigma^2_m(s,g,u))$ and $q^u(u|s,g,a) = \mathcal{N}(\mu_u(s,g,a), \sigma^2_u(s,g,a))$. The corresponding decoders are defined as $d^m(m) = (\hat{s},\hat{g},\hat{u})$ and $d^u(u) = (\hat{s},\hat{g},\hat{a})$. Let $\mathcal{D}_{SCM}$ be a set of trajectories used to learn the SCM (we discuss in section 4.1 the choice of the training trajectories for the SCM). To learn the SCM from the observed trajectories in $\mathcal{D}_{SCM}$, we alternate between optimizing the following two losses:

$$\mathcal{L}^u_{SCM} = \mathbb{E}_{u\sim q^u(u|s,g,a),s,g,a\sim\mathcal{D}_{SCM}} ||(d^u(u) - (s,g,a))||^2 + \mathbb{KL}(q^u(u|s,g,a)\|\mathcal{N}(0,1)) \quad (4)$$

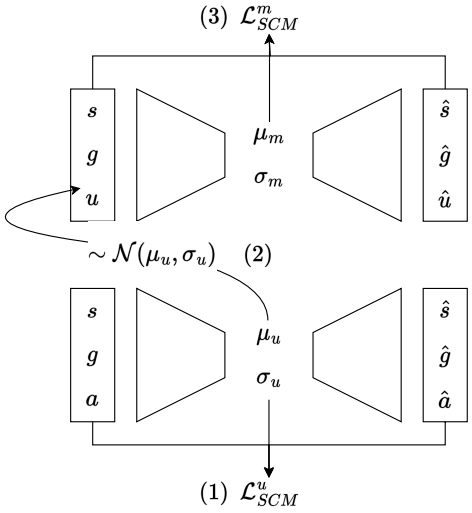


Figure 2: The three steps of the SCM learning loop: (1) Update u's VAE. (2) Sample u batch from the updated distribution. (3) Update m's VAE.

$$\mathcal{L}^m_{SCM} = \mathbb{E}_{m\sim q^m(m|s,g,u),u\sim q^u(u|s,g,a),s,g,a\sim\mathcal{D}_{SCM}} ||(d^m(m) - (s,g,u))||^2 + \mathbb{KL}(q^m(m|s,g,u)\|\mathcal{N}(0,1)) \quad (5)$$

In each iteration, we sample a u batch from the updated distribution $q^u(s,g,a)$ to use as input to the VAE corresponding to m. This is essential to learn the dependencies between the exogenous variable m and the motivator m. Figure 2 summarizes the SCM learning steps.

3.2.2 Generating Counterfactual Data

Once we have approximated the SCM, we can generate counterfactual data points following the steps in section 2.3. Let e_m and e_u denote the functions giving the deterministic VAEs' outputs, *i.e.* the learned distributions' means: $e_m(s,g,u) = \mu_m(s,g,u)$ and $e_u(s,g,a) = \mu_u(s,g,a)$. For a given triplet (s,g,a), we denote the corresponding motivator as $m_{s,g} = e_m(s,g,e_u(s,g,a))$. Given an alternative goal g', we denote the corresponding counterfactual motivator as $m^{g'}_{s,g}$. To predict $m^{g'}_{s,g}$, we use e_u to recover the noise term from the observed evidence (s,g,a) and we inject it in the structural equation (3) where we also set the goal to $g\prime$. The predicted counterfactual motivator can then be written as:

$$m^{g'}_{s,g} = e_m(s,g',e_u(s,g,a)) \quad (6)$$

Figure 3 summarizes the counterfactual data generation steps.

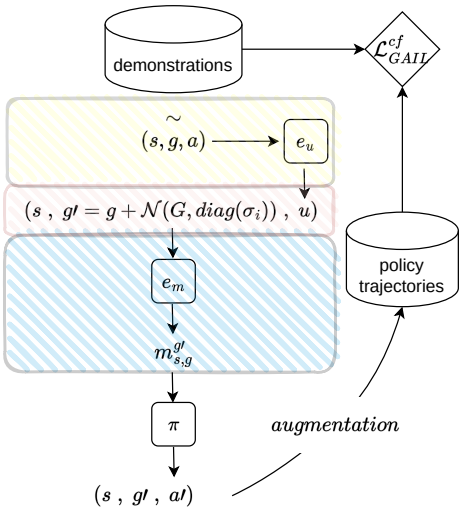


Figure 3: Counterfactual data generation: The yellow, red and blue boxes denote the abduction, intervention and prediction steps respectively.

4 POLICY LEARNING WITH CAUSAL REASONING

We base our approach on GoalGAIL. GoalGAIL optimizes equation (2) by alternating between two steps: learning the reward function and optimizing the policy. In the first step, the discriminator is trained to minimize the GAIL loss:

$$\mathcal{L}_{GAIL} = \mathbb{E}_{s,g,a\sim\mathcal{D}_\pi}[\log D(s,g,a)] + \mathbb{E}_{s,g,a\sim\mathcal{D}_E}[\log(1-D(s,g,a))] \quad (7)$$

where $\mathcal{D}_\pi$ denotes the trajectories generated by the current version of the policy, *i.e.* the on-policy data. For the second step, the policy is optimized using any RL algorithm, with respect to the following reward $r = D(s,g,a)$.

In our approach, we start by pretraining the SCM from expert demonstrations. Then, as we learn the policy and the reward, we keep finetuning the learned SCM. The learned SCM is used at each step to generate counterfactual data for reward learning. For policy learning, the only difference is that it is no longer conditioned on the state-goal pairs but rather on the causal motivator learned by the SCM. In the following, we detail each of these three steps.

4.1 Pretraining and Finetuning the SCM

At the beginning of the learning process, we want to capture all the causal information in the available demonstrations. We fit the two VAEs discussed in 3.2 on the expert demonstrations. In this step, $\mathcal{D}_{SCM}$ in equations (4) and (5) is set to $\mathcal{D}_E$. However, the available demonstrations are usually limited and insufficient to learn complex patterns of the SCM. To alleviate this problem, at each iteration, we finetune the VAEs on data from both the expert demonstrations and the trajectories generated by the current policy. $\mathcal{D}_{SCM}$ is then set to $\mathcal{D}_E \cup \mathcal{D}_\pi$. As we update the policy, the quality of its trajectories improves, which benefits the SCM. Policy trajectories prevent the SCM from overfitting to the limited demonstration data without decreasing the performance.

4.2 Learning the Reward with Counterfactual Demonstrations

In GoalGAIL, the discriminator is optimized to learn to distinguish expert trajectories from those generated by the policy. While adversarial imitation learning provides a direct way to learn from demonstrations and bypass the intermediate step in IRL, they inherently suffer from the instability of the learning process as in GANs (Arjovsky and Bottou, 2017). Such a problem is even more severe in adversarial imitation learning because **1)** expert data is very limited and **2)** the generator, *i.e.* the policy, is trained by policy gradient (Sutton et al., 1999) and not by simple gradient descent as in GANs. Adversarial training of GANs is unstable because it requires a balance between the discriminator and the policy, which is hard to achieve, especially at the beginning of the learning. In early iterations, the trajectories generated by the policy are random, which makes them easily distinguishable by the discriminator. This leads to having a too-powerful discriminator, making its feedback uninformative for the policy. Another problem is that of mode collapse. Mode collapse occurs when the generator, *i.e.* the policy, outputs a narrow set of trajectories instead of exploring the whole policy space. This problem is more likely to occur when the training data is limited.

We show that counterfactual examples can help mitigate the problems mentioned above. Since the SCM learns the expert behavior, it is natural to generate counterfactuals from expert demonstrations rather than policy rollouts. An intuitive way to use these counterfactual examples is to add them as supplementary demonstrations. However, it is more efficient to use such counterfactual demonstrations to augment policy data. In fact, given the low quality of counterfactuals compared to real expert demonstrations, adding them to the demonstrations may in fact decrease the performance. However, these counterfactuals could serve well as policy data.

To understand the intuition behind such a claim, we should recall that the counterfactual data is more difficult to classify for the discriminator because it resembles the expert demonstrations at the motivator level. This can mitigate the first problem mentioned above by preventing the discriminator from being too powerful in classifying trajectories. This is in line with work in supervised learning showing that learning from difficult examples is more efficient (Robinson et al., 2021). Furthermore, by adding counterfactuals, the policy data becomes more diverse, which helps prevent mode collapse. It is also worth noting that as the policy improves, the quality of counterfactuals improves, and classifying them becomes even more difficult. The discriminator output then becomes more and more informative for the policy. We show in the experiments that this allows learning better reward functions.

The modified GAIL loss then becomes:

$$\mathcal{L}^{cf}_{GAIL} = \mathbb{E}_{s,g,a\sim\mathcal{D}_\pi\cup\mathcal{D}^{\text{cf}}_\pi} \log D(s,g,a) + \mathbb{E}_{s,g,a\sim\mathcal{D}_{expert}} \log(1-D(s,a,g)) \quad (8)$$

where $\mathcal{D}^{\text{cf}}_\pi$ denotes the counterfactual policy data. This corresponds to $\mathcal{D}_\pi$ with every data point relabeled counterfactually as explained in 3.2 using alternative goals sampled by adding Gaussian noise with variance σ^2 to the original ones: $\mathcal{D}^{\text{cf}}_\pi = \{(s,g\prime,a\prime = \pi(s,m^{g\prime}_{s,g}), g\prime \sim \mathcal{N}(g, diag(\sigma)), (s,g) \sim \mathcal{D}_\pi\}$

4.3 Learning the Policy

The policy is optimized using an RL algorithm with respect to the reward output by the discriminator. To benefit from HER, we use an off-policy algorithm, namely DDPG (Lillicrap et al., 2015), as in the original GoalGAIL work. In our setting, the policy input is no longer the state and goal pairs, but rather the motivator m inferred from (s,g,u). When learning the SCM, u is sampled from the distribution output by the u's VAE encoder for a given (s,g,a) triple. However, when learning the policy or interacting with the environment, we only have access to (s,g). We overcome this problem by using the average mean output by u's VAE encoder across all the trajectories generated by both the policy and the expert. We denote this inference noise term as μ^*_u. The predicted actions then become $a = \pi(e_m(s,g,\mu^*_u))$. Consequently, DDPG's Q-function becomes:

$$\mathcal{L}_Q = \mathbb{E}_{(s,g,a,s')\sim\mathcal{R}}[(Q(s,g,a) - (D(s,g,a) + \gamma Q(s', \pi(s', g, \pi(s', g, \mu^*_u))))^2] \quad (9)$$

where s' denotes the next state reached after taking action a in state s and $\mathcal{R}$ denotes the policy replay buffer containing all the trajectories generated by the policy since the beginning of the learning. Similarly, DDPG's policy objective becomes:

$$J_\pi = \mathbb{E}_{s\sim\pi}[Q(s, \pi(s,g,\mu^*_m))] \quad (10)$$

Algorithm 1 summarizes the entire approach.

Input: Random π, Demonstrations set $\mathcal{D}_E$, Empty buffers $\mathcal{R}$, $\mathcal{D}_{SCM}$ and $\mathcal{D}_\pi$
`// SCM pretraining`
$\mathcal{D}_{SCM} \leftarrow \mathcal{D}_E$
for *k=1 to n* **do**
  Update SCM using eq. (4) and (5)
end
`// Policy Learning Loop`
for *k=1 to m* **do**
  `// Interaction with the Environment`
  $\mathcal{D}_\pi \leftarrow \{(s,g,a) \sim \pi\}$
  $\mathcal{R} \leftarrow \mathcal{R} \cup \mathcal{D}_\pi$
  `// SCM Finetuning`
  $\mathcal{D}_{SCM} \leftarrow \mathcal{D}_E \cup \mathcal{D}_\pi$
  Update SCM using eq. (4) and (5)
  `// Counterfactuals Generation`
  $\mathcal{D}^{\text{cf}}_\pi \leftarrow \{(s,g\prime,a\prime = \pi(s,m^{g\prime}_{s,g}), g\prime \sim \mathcal{N}(g, diag(\sigma)), (s,g) \sim \mathcal{D}_\pi\}$
  `// Reward Update`
  Minimize $\mathcal{L}^{cf}_{GAIL}$ in eq. (8)
  `// Policy Update`
  Update Q-function using eq. (9)
  Update π using eq. (10)
end

Algorithm 1: Overview of the proposed approach.

5 EXPERIMENTAL RESULTS

We conduct experiments in a simulated environment featuring a 7-DoF Fetch Mobile Manipulator arm with a two-fingered parallel gripper (Plappert et al., 2018). We tackle three diverse manipulation tasks. **1) Push:** The agent's mission is to move a box by pushing it along a table, guiding it to reach a predetermined goal position. **2) Pick and Place:** The agent has to grasp a box from a table using its gripper and then move it to a designated goal position. **3) Push:** The agent's task is to hit a puck resting on a table in such a way that it slides and comes to a halt at the specific goal position.

Our experiments aim to address three key questions. **1)** Does our method improve the agent's performance compared to the baseline (GoalGAIL)? **2)** What impact does the incorporation of counterfactual data have on the learned reward function? **3)** Can

our method perform efficiently with fewer demonstrations?

5.1 Sample Efficiency

To assess the effectiveness of our approach, we present in Figure 4 the learning curves for each of the three tasks with 10 expert demonstrations. The curves illustrate the success rate achieved by both GoalGAIL and our method over the course of the training. The success rate is computed over 10 test episodes, and the curves show the mean and standard deviation of the results averaged over 5 independent random seeds.

The obtained learning curves show that our method consistently outperforms GoalGAIL in terms of both final success rate and convergence speed across all three tasks. This suggests that the performance gain can be attributed to our method's ability to leverage counterfactual data. To gain deeper insights into how the counterfactual data affects the learning process, we examine the difference between the reward functions learned by our method and the baseline.

5.2 Learned Rewards with Counterfactuals

In this section, we focus our analysis on the Pick and Place task with 10 expert demonstrations. We dissect the influence of counterfactual data on the learned reward function.

Figure 5 presents the evolving reward distributions learned by the discriminator in both our method and the baseline for expert demonstrations and trajectories generated by the policy. The plotted reward distributions unveil several noteworthy observations. Firstly, our method exhibits a reward distribution that is notably flatter and less skewed compared to the baseline. Furthermore, our approach tends to output rewards that are generally less optimistic overall. This is evident when examining the distribution centroids at convergence for expert demonstrations, where our method's reward distribution centers around approximately 0.6 (Figure 5c), in contrast to the baseline's which centers around approximately 0.9 (Figure 5a). Similarly, for policy-generated trajectories, our method's rewards span the whole reward space (Figure 5d) while the baseline's rewards are predominantly concentrated above 0.5 (Figure 5b).

These observations suggest that counterfactual data acts as a regularizer preventing the overestimation of the reward. Due to the way we generate counterfactual data using the learned SCM, its quality resembles that of the expert demonstrations, preventing the discriminator from confidently distinguishing between the two. This in turn curbs the discriminator's tendency to assign overly optimistic rewards as we can observe with the baseline. The resulting reward distribution makes the discriminator's feedback more informative to the policy which explains the improved performance and expedited convergence observed in our approach.

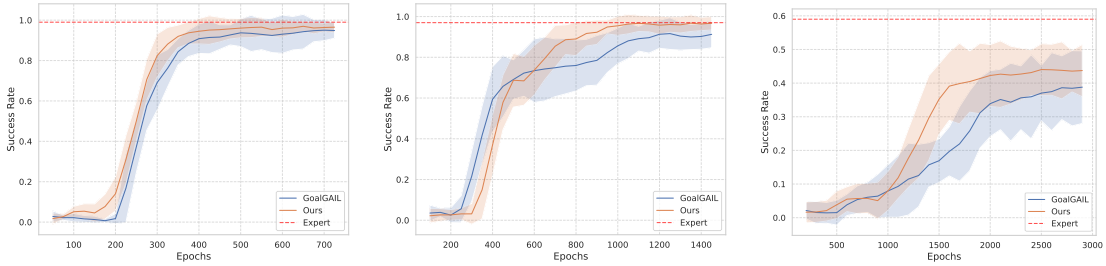
We further examine the reward dynamics across various trajectory types: expert demonstrations, successful policy trajectories, and failed policy trajectories. We randomly select one representative trajectory from each category and plot the reward predictions generated by both GoalGAIL and our method at each timestep along these trajectories. The obtained results shown in Figure 6 are in line with the earlier observations regarding the more conservative nature of the reward in our method compared to the baseline. Additionally, our approach maintains a higher degree of reward consistency throughout the trajectory, in contrast to the baseline's oscillatory reward predictions.

5.3 Low Data Regime

In this section, we conduct experiments to assess the robustness of our method in the face of a reduced number of demonstrations. In Figure 7, we present the success rate achieved at convergence for the Pick and Place task, averaged across 5 independent runs, as we vary the number of expert demonstrations given to the agent. The results show that our method consistently outperforms the baseline. More importantly, our method exhibits a milder decline in performance as the number of demonstrations decreases when contrasted with the baseline.

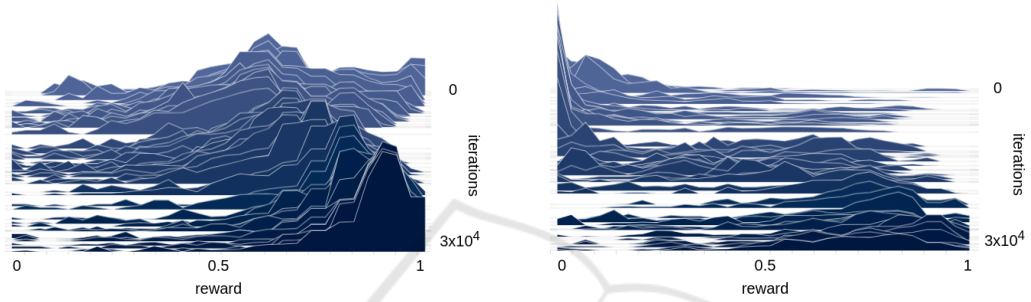
6 CONCLUSION

In this paper, we have presented a novel approach to enhance the efficiency and effectiveness of generative adversarial imitation learning in goal-conditioned tasks. Our method leverages the power of Structural Causal Models to improve the learning process. By learning the causal mechanism governing a high-level behavior policy of the demonstrator, we are able to generate counterfactual data that we use as additional training data for the reward function. Our experiments show that the incorporation of counterfactual data mitigates reward overestimation and improves its informativeness for policy learning. This results in superior performance and faster convergence compared to the baseline. Moreover, our methods perform well in scenarios with limited expert demonstrations



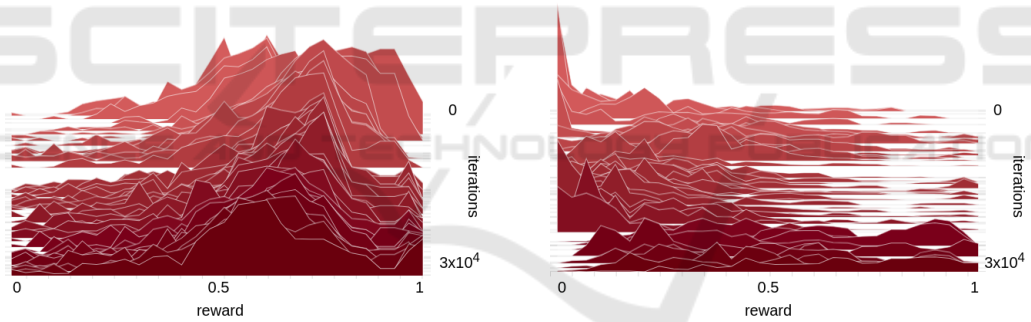
(a) Push. (b) Pick and Place. (c) Slide.

Figure 4: Learning curves of our approach and the baseline for different tasks: Our approach boosts the final performance of GoalGAIL and accelerates convergence across all three tasks.



(a) GoalGAIL reward distribution for expert demonstrations.

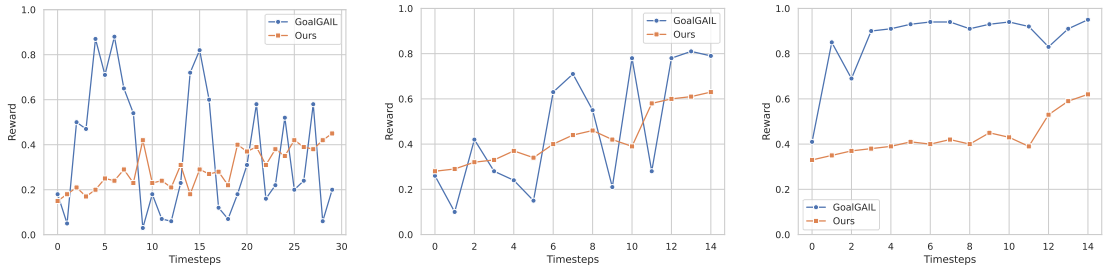
(b) GoalGAIL reward distribution for policy trajectories.



(c) Our approach's reward distribution for expert demonstrations.

(d) Our approach's reward distribution for policy trajectories.

Figure 5: The distribution of the rewards learned by our approach and the baseline: Our method mitigates reward overestimation and demonstrates flatter, less skewed reward distributions for both expert demonstrations and policy trajectories.



(a) Failed trajectory. (b) Successful trajectory. (c) Expert demonstration.

Figure 6: Reward predictions by our approach and the baseline for different types of trajectories: The reward output from our method exhibits greater consistency throughout trajectory execution.

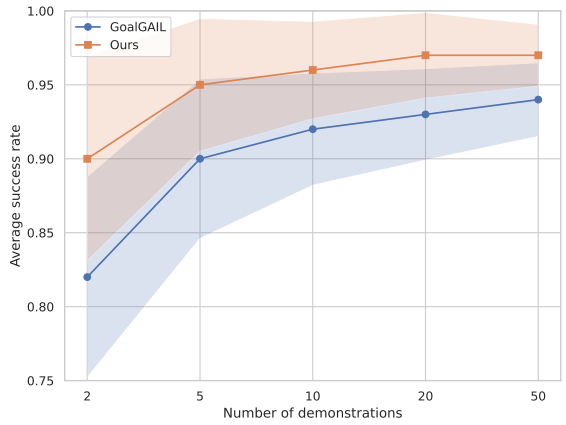


Figure 7: Average success rate for different numbers of demonstrations: Our method is more resilient to the decrease of the number of demonstrations.

and make a step toward achieving more reliable imitation learning using causality.

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