STRUCTURAL GENERALIZATION OF VISUAL IMITATION LEARNING WITH POSITION-INVARIANT REGULARIZATION

Anonymous authors
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ABSTRACT

How the visual imitation learning models can generalize to novel, unseen visual observations is a highly challenging problem. Such a generalization ability is very crucial for their real-world applications. Since this generalization problem has many different aspects, we focus on one case called *structural generalization*, which refers to generalization to unseen task setup, such as a novel setup of object locations in the robotic manipulation problem. Previous works observe that the visual imitation learning models in this case will overfit to the absolute information (e.g. coordinates) rather than the relational information between objects, which is more essential for decision making. As a result, the models will perform poorly in novel scenarios. Nevertheless, so far it remains unclear how we can solve this problem effectively. Our insight to this problem is to explicitly remove the absolute information from the features learned by imitation learning models, so that the models can use robust, relational information to make decisions. To this end, we propose a novel, position-invariant regularizer for generalization. The proposed regularizer will penalize the imitation learning model when its features contain absolute, positional information of objects. We carry out experiments on the MAGICAL and ProcGen benchmark, as well as a real-world robot manipulation problem. We find that our regularizer can effectively boost the structural generalization performance of imitation learning models. Through both qualitative and quantitative analysis, we verify that our method does learn robust relational representations.

1 INTRODUCTION

Imitation learning is a class of algorithm that enables robot to acquire behaviors from human demonstrations (Hussein et al., 2017). The recent advance of deep learning has boosted the development of vision-based imitation learning, and supported its applications like autonomous driving, robotic manipulation, and human-robot interaction (Hussein et al., 2017).

In spite of its success, vision imitation learning methods still face many practical challenges. One major challenge is its ability to generalize to novel, unseen visual observations, which is very common when we deploy the trained models (Toyer et al., 2020; Park et al., 2021). In the literature, this generalization problem is also known as the robustness problem. The problem covers many different aspects. Here, we categorize the *visual generalization* into two different types: *observational generalization* and *structural generalization* (Figure 1). Observational generalization refers to the generalization to novel visual textures. The changes of background color, the object texture, or ambient light in the robotic manipulation task are examples of observational generalization. Such kind of visual change does not affect the underlying task structure (e.g. the position of object and targets), and only requires the robot to reason about semantic meanings correctly. In contrast, structural generalization refers to the generalization to unseen task setup, which is much more essential. Consider the task of letting a warehouse robot to move a box to some target region. If we set the initial position of the box to a place that is not covered by the demonstration dataset, then the imitation learning methods must be able to perform structural generalization so as to succeed. In reality, the generalization challenge usually emerges as a combination of both the observational and structural generalization. In this paper, *we focus on the study of structural generalization*.

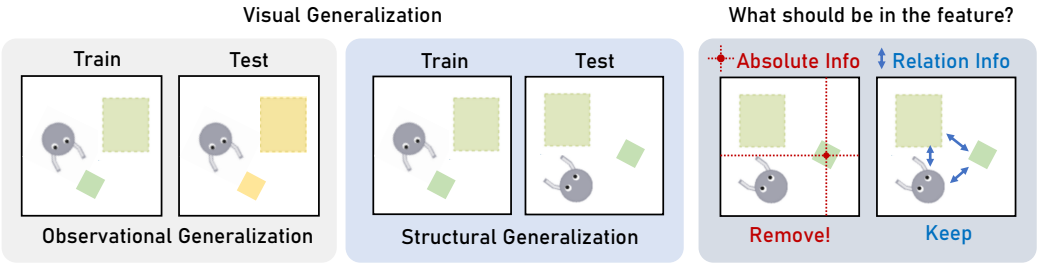

Figure 1: **Left and Middle:** Two kinds of visual generalization. The examples are based on the MAGICAL benchmark provided by Toyer et al. (2020), in which a robot is required to relocate a box to a target region. The left figure shows an example the observational generalization, in which the only change during the testing phase is the visual texture of objects. The middle figure shows an example of structural generalization. The object setup in the testing phase is unseen. **Right:** To achieve structural generalization, we suggest that absolute information should be removed from the feature, while the relational information should be kept. We propose a novel, position-invariant regularizer for this purpose.

To achieve structural generalization, the vision imitation learning models should be able to obtain knowledge about objects and their spatial relations with proper inductive biases. Some work finds that vanilla deep vision models strongly overfit to the absolute position of objects (Toyer et al., 2020), which suggests that they do not extract relational information of objects to make decisions like humans (Doumas et al., 2022). Since the representation learning methods can usually lead to good semantic representations (features) and lead to generalization, Chen et al. (2021) investigate the use of self-supervised representation learning methods in visual imitation learning. However, they find that these general-purpose representations fail to improve the generalization performance of vanilla vision imitation learning models effectively. Aside from these works, we also notice that some works propose variants of vision transformers (Dosovitskiy et al., 2021) to improve structural generalization (Yuan et al., 2021), though these methods are not for imitation learning. Moreover, they make additional assumptions such as the availability of object information. So far, it remains unclear how to ensure structural generalization in imitation learning.

Based on these observations, our main insight to this problem is to explicitly remove the absolute, positional information from the learned features in the vision imitation learning models. Note that this does not mean that the decision making process is not dependent on the absolute information. Rather, we expect that the model can extract the relational information (e.g. distance, direction) from the absolute information to make robust decisions. To this end, we propose a novel position-invariant regularizer called POINT. This regularizer will penalize the imitation learning model when it finds that the learned feature highly correlates with absolute, positional information. As a result, the imitation learning model has to discover more robust, relational features. To validate our idea, we test the proposed regularizer on the MAGICAL (Toyer et al., 2020) and ProcGen (Cobbe et al., 2020) benchmark, as well as a real-world robot manipulation problem. We find that our method can effectively improve the structural generalization performance. Furthermore, we conduct qualitative and quantitative analysis and find that the imitation learning models can indeed learn relational features with our proposed regularizer.

To summarize, our contributions in this paper are as follows.

- We define the structural generalization problem of visual imitation learning models and propose a novel position-invariant regularizer called POINT to tackle this problem.
- We test our method on MAGICAL and ProcGen benchmark, as well as a real-world robot manipulation problem. We find that our proposed regularizer can improve the structural generalization performance of previous imitation learning models effectively.
- Through qualitative studies, we verify that our proposed regularizer does make the visual imitation learning models extract relational information.

2 RELATED WORK

Imitation Learning Imitation learning (IL) is a classical method to solve the sequential decision-making problems with expert demonstration data. Existing imitation learning methods are consisted of two classes of algorithms: behavioral cloning Bain & Sammut (1995) and inverse reinforcement learning Ng et al. (2000). Behavioral cloning is a supervised learning method which directly fits expert's actions. Inverse reinforcement learning instead proposes to infer a reward function from the expert's demonstration, and use it to train an RL agent. Both of these methods suffer from the generalization problem discussed above. In this paper, we mainly focus on the behavioral cloning since it is simple and do not involve dangerous online interactions like IRL (Park et al., 2021).

Generalizable Policy Learning The generalization problem of the imitation learning has been a long-standing problem. Since the problem also exists in the reinforcement learning and most of the solutions can be adapted to the case of imitation, we discuss the works from both of the fields here. One existing branch of work is the *domain randomization* (Tobin et al., 2017). The basic idea of domain randomization is to collect data from diverse setups, such as different background and textures. As a result, the trained model will be able to discover more robust features. Resembling this idea, another line of works try to solve this problem with *data augmentation*, which augment the input or the learned features according to some heuristics. For example, MixReg (Wang et al., 2020) proposes a mixture augmentation method and find that it can lead to better out-of-distribution generalization. OREO (Park et al., 2021) proposes to use a mask out the objects in the feature map, so that the model will not fit a specific object in the observation. CLOP (Bertoin & Rachelson, 2022) finds it important to shuffle the feature map locally to ensure the robustness. Though not exactly a data augmentation approach, (De Haan et al., 2019) proposes to randomly mask out the semantic components in the feature space and see whether they are correlated with correct expert actions.

Aside from works using diverse data or data augmentation, some works also approach this problem by incorporating proper inductive biases into the design of policy networks. For instance, SORNet (Yuan et al., 2021) uses a variant of vision-transformer to solve robotics tasks that requires relational reasoning. However, SORNet is not aimed at imitation learning or reinforcment learning. Zhou et al. (2022) proposes to use a attentional architecture to solve a compositional, object-centric reinforcement learning problem. The idea of these methods is to leverage the relational inductive bias of the attention operations. Wen et al. (2022) proposes PrimeNet, which introduces a short cut into the neural network to ensure that the model focus on more meaningful area.

Representation learning methods are another approach for generalization. Some works use pre-trained representation. For instance, Yen-Chen et al. (2020) uses a pretrained model on MS-COCO dataset (Lin et al., 2014) to provide representation for imitation learning in robotics manipulation. The pretrained model over large datasets provides more robust object representations and can generalize the policy to unseen objects. Besides pretrained representation, self-supervised representation learning Mandi et al. (2022); Chen et al. (2021) on the demonstration dataset only can also improve the generalization in some cases. However, Chen et al. (2021) suggests that self-supervised representation do not improve the generalization performance in general.

Our work differentiates from all these existing works by explicitly defining the structural generalization problem and proposing to remove the nonrobust positional information from the representation.

3 PRELIMINARIES

Notations We model the sequential decising making problem as Markov Decision Process $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{T})$. $\mathcal{S}$ is the state space. $\mathcal{A}$ is the action space. $\mathcal{R}$ is the reward function. $\mathcal{T}$ is the transition dynamics. The agent's state at timestep t is $s_t \in \mathcal{S}$. The agent takes action a_t and receives reward $r_t = \mathcal{R}(s_t, a_t)$. Its state at timestep $t+1$ is then $s_{t+1} \sim \mathcal{T}(s_t, a_t)$. The objective of the agent is to maximize the return $\sum_{t=0}^{T} \gamma^t r_t$, where γ is a discount factor.

For the imitation learning problem studied here, the agent has no access to $\mathcal{R}$ and $\mathcal{T}$, but it is provided with a fixed expert demonstration dataset $\mathcal{D} = \{\tau_i\}$. Here, each $\tau_i = (s_0^E, a_0^E, s_1^E, a_1^E, ...s_T^E, a_T^E)$ is an expert trajectory that can achieve high performance in $\mathcal{M}$. Therefore, the agent should learn the behavior by leverage the given demonstration dataset.

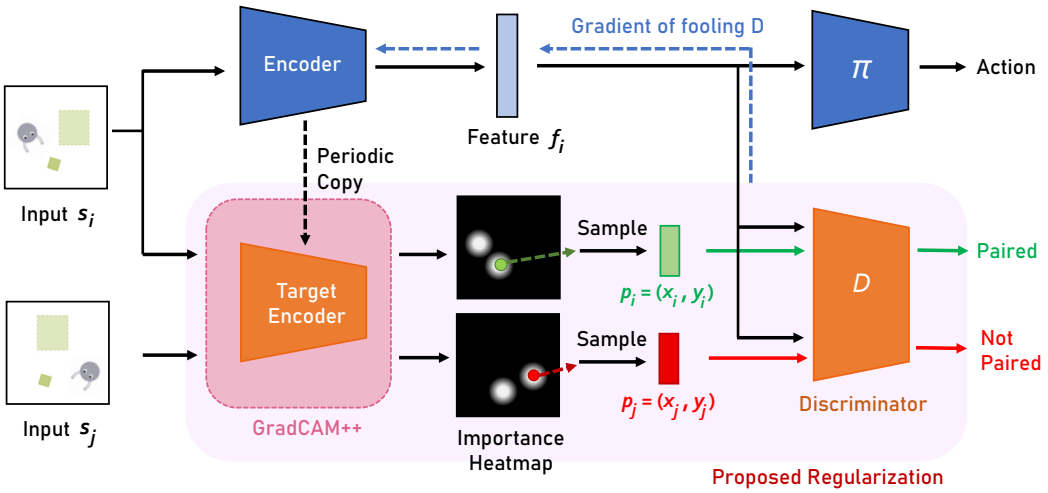

Figure 2: Overview of our method. The above branch is the common imitation learning pipeline. Our proposed regularizer is shown in the light pink box at the bottom. The regularizer first uses the GradCAM++ algorithm to find out the important areas based on which the latest model make decisions. Then it samples the coordinates from the discovered important areas, and uses a discriminator network D to calculate whether these sampled coordinates are paired with features f. The model (encoder) is then trained to fool the discriminator D. When the encoder is able to fool D, the absolute positional information is removed from the feature as desired.

Behavioral Cloning One classical imitation learning algorithm is the Behavioral Cloning (BC). BC turns the imitation learning problem to a supervised learning problem. It fits the expert's action a_i given the observation s_i. For the visual imitation learning problem, the BC model can be divided into two consecutive parts: a vision encoder f_θ (which is usually a convolutional neural network), and a policy head π. The f_θ first encodes s_i to the feature $f_i = f_\theta(s_i)$, and the π then uses it to predict the expert's action. The BC algorithm minimizes the following negative log-likelihood objective:

$$\mathcal{L}_{BC} = \mathbb{E}_{(s_i,a_i)\in\mathcal{D}} \left[-\log \pi(a_i | f_\theta(s_i)) \right].$$

Due to its simplicity, BC is widely used in visual imitation learning. Therefore, we study the structural generalization on BC in this paper.

GradCAMs Gradient-weighted Class Activation Mapping (GradCAM) (Selvaraju et al., 2017; Chattopadhay et al., 2018) is a class of algorithms that can intepret the deep vision models by visualizing the importance region for decision making. Its basic idea is to calculate the gradient at each feature map, and aggregate them into an importance map. In this paper, we leverage GradCAM as a rough object detector in the proposed regularizer. We refer readers to the original paper for more technical details.

4 Method

In this section, we present our position-invariant regularizer for the structural generalization. As is discussed before, our basic idea is to remove the absolute positional information from the features of BC model. In the following parts, we first present a formalized description of the idea and its practical challenges in the section 4.1. Then, we discuss how to handle these challenges with GradCAM and adversarial training in the section 4.2 and 4.3. Finally, we provide a summary of the overall algorithm in the section 4.4. We illustrate our method in the Figure 2 and provide the pseudo code in the Algorithm 1.

4.1 Formulation and Challenges

For the tasks that involves structural generalization, there usually exist multiple objects in the observed states, such as the agent, the target object, and the goal. For the state s_i, we denote each

of these objects in s_i as o_i^j, and their positions as (x_i^j, y_i^j). Then, our idea can be formulated as the minimization problem of each $I((\mathbf{x}^j, \mathbf{y}^j), \mathbf{f})$, where I is the mutual information. Note that we use the notation $\mathbf{x}, \mathbf{y}, \mathbf{f}$ to indicate the corresponding random variables of x_i^j, y_i^j, f_i. However, this formulation leads to many practical challenges. First, since each (x_i^j, y_i^j) is not provided directly by s_i and should be inferred, we have to either train some object key-point detectors to detect the underlying objects in the training set, or annotate the objects by ourselves. However, both of these approaches can be difficult and tedious in practice. Second, even if we have ideal key-point detectors, we have to deal with a hard optimization problem in the summation form $\sum_j I((\mathbf{x}^j, \mathbf{y}^j), \mathbf{f})$. This can be intractable when there are many objects presents.

Fortunately, we find that the previous works on the interpretation of deep learning models like GradCAM provide useful tools to handle these challenges. It can reduce the problem to a much simpler form. We discuss our observations as follows.

4.2 Problem Reduction with GradCAM

GradCAM is a interpretation method that can tell which part of the image is crucial in the decision process of a deep learning model. Given a model f_θ and input s, GradCAM outputs an importance heatmap of the same resolution as the input s. The heatmap indicates the importance of each pixel when we use current model f_θ for prediction. One nice property of this generated heatmap is that it is smooth and usually coincides with the meaningful objects in the current scene. Therefore, we can consider the GradCAM as a rough object detector here.

We propose to sample $p_i = (x_i, y_i)$ from the generated heatmap, and then minimize the $I(\mathbf{p}, \mathbf{f})$. We find that this new objective can act as a proxy of the original objective in practice. Concretely, if p_i is always far from a specific object like o^k, then we know that o^k is irrelevant to the decision process of current model. In this case, we conjecture that $I((\mathbf{x}^k, \mathbf{y}^k), \mathbf{f})$ should be low enough to meet our requirement. On the contrary, if p_i always coincides with a certain object like o^l, then we actually minimize $I(\mathbf{p}, \mathbf{f}) \approx I((\mathbf{x}^l, \mathbf{y}^l), \mathbf{f})$ as we want.

4.3 Implementing the Loss Function

Now, our remaining work is to reduce the mutual information $I(\mathbf{p}, \mathbf{f})$. However, we find that jointly estimating and minimizing the mutual information in our vision-based tasks is hard in practice. Since our ultimate goal is to minimize the information of $\mathbf{p}$ in $\mathbf{f}$, we instead propose an adversarial training framework to achieve this goal.

Specifically, we introduce a discriminator network D to play a two-player min-max game with the BC model as follows.

$$\min_{f_\theta} \max_{D} \mathbb{E}_{(s_i,a_i)\sim\mathcal{D},(s_j,a_j)\sim\mathcal{D}} \left[\log D(p_i, f_i) + \log(1 - D(p_j, f_i))\right]. \tag{1}$$

In this min-max game, the discriminator D tries to tell the joint distribution of $\mathbf{p}$ and $\mathbf{f}$, denoted as $\mathbb{P}_{\mathbf{p},\mathbf{f}}$, from the product of their marginal distributions $\mathbb{P}_{\mathbf{p}\otimes\mathbf{f}}$. Meanwhile, the BC model is trying to fool the discriminator by removing the information of $\mathbf{p}$ from $\mathbf{f}$. Applying the convergence theory of the generative adversarial network (GAN) (Goodfellow et al., 2020), we know that when f_θ is a global minimizer of Equation 1, $\mathbb{P}_{\mathbf{p},\mathbf{f}} = \mathbb{P}_{\mathbf{p}\otimes\mathbf{f}}$, which implies that $I(\mathbf{p}, \mathbf{f}) = 0$. Therefore this min-max game fulfills our requirement.

In practice, we train D to minimize the following binary lass classification loss function:

$$\mathcal{L}_D = -\mathbb{E}_{(s_i,a_i)\sim\mathcal{D},(s_j,a_j)\sim\mathcal{D}} \left[\log D(p_i, f_i) + \log(1 - D(p_j, f_i))\right]. \tag{2}$$

However, for the encoder f_θ, we find that using $-\mathcal{L}_D$ as the loss function for training will result in instabilities. We assume that this is because f_i term presents in both of the two terms in the Equation 2, which is different from that in the original GAN objective. Therefore, we propose to use the following loss function for optimization, which we find works well empirically:

$$\mathcal{L}_{reg} = \mathbb{E}_{(s_i,a_i)\sim\mathcal{D}} \left[\log D(p_i, f_i)\right]. \tag{3}$$

Combining the BC loss, the loss function to train the f_θ and π is then

$$\mathcal{L} = \mathcal{L}_{BC} + \lambda\mathcal{L}_{reg} = \mathbb{E}_{(s_i,a_i)\sim\mathcal{D}} \left[-\log \pi(a_i|f_\theta(s_i)) + \lambda \log D(p_i, f_i)\right]. \tag{4}$$

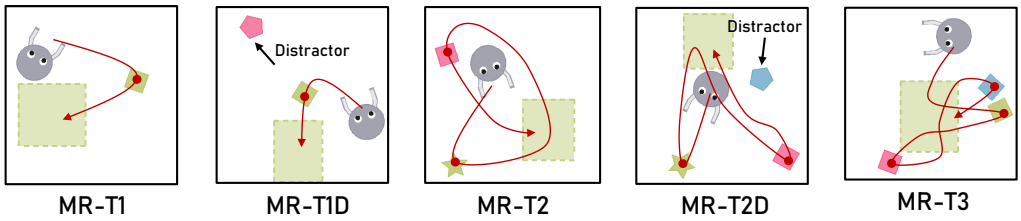

Figure 3: The MAGICAL tasks used in our experiments. They grey robot is required to move the target objects (we mark them by red dots) to the target region. The red curve shows a possible plan to solve the task (the interaction details like releasing box are omitted). The long horizontal nature of this task brings additional challenges aside from the structural generalization problem.

4.4 Summary of the Algorithm

Finally, we put everything together and summarize our algorithm in Algorithm 1. We use GradCAM++ (Chattopadhay et al., 2018), an improved version of GradCAM to calculate the heatmap. We find that it can deal with multi-object observation better than GradCAM. Similar to the target network in the deep reinforcement learning, we propose to use a target encoder model in the GradCAM calculation. This target encoder model periodically copies the weights of the latest encoder model. This ensures that the p_i in the Equation 1 will change slowly throughout the training, so that the optimization of the min-max game between D and f_θ becomes stable.

Algorithm 1: POINT

Initialize parameters of BC model: f_θ, π, and the discriminator D. Initialize target encoder $\tilde{f}_\theta$ using weights of f_θ.
while *not converged* **do**
  Sample an initial state $s_0 \sim p(s_0)$.
  Sample a batch $\{(s_i, a_i)\}$ from $\mathcal{D}$.
  Calculate each importance heatmap by $H_i = \mathrm{GradCAM}(\tilde{f}_\theta, s_i)$.
  Sample each p_i from H_i.
  Optimize the BC model by Eqn. 4.
  Optimize the discriminator by Eqn. 3.
  Update the $\tilde{f}_\theta$ using f_θ.

5 Experiments

In the experiments, we first test the performance of our method on two benchmarks that require structural generalization: MAGICAL and ProcGen. Then, we provide analysis of our algorithm through both qualitative and quantitive studies. Finally, we extend our method to a real robot manipulation problem.

5.1 Task Setup

MAGICAL The MAGICAL benchmark simulates a 2D robotic manipulation problem in a warehouse room. The tasks provided by the MAGICAL involve complex interactions between the agent and multiple objects, which require effective structural generalization.

In the experiments, we use a variant of its MatchRegion task. In this task, a robot is required to go across a square room to move some objects to a target region specified by a dashed rectangle. We setup several task instances of the MatchRegion task: MatchRegion-Target-1, MatchRegion-Target-2, MatchRegion-Target-2-Distract, MatchRegion-Target-3, MatchRegion-Target-3-Distract. We provide an illustration of these tasks in the Figure 3. For each MatchRegion-Target-X task (MR-TX), there is no distractor object in the room, so the robot only needs to move all the X objects into the target location. However, for the MatchRegion-Target-X-Distract task (MR-TXD), there is an additional distractor object in the room. This object is also randomly setup in the room during testing. The existence of this distractor object not only increases the risk of learning spurious features but also add to the difficulty of learning secure motions. As we will discuss later, even the existence of one distractor object can lead to a significant increase of generalization difficulty. The study of more distractors is carried out in the analysis part.

Table 1: Evaluation result on the MAGICAL and ProcGen benchmark. We show the average score on three random seeds. Our method can achieve the state of the art result compared with the baselines.

Method	Vanilla	Dropout	Cutout	MixReg	OREO	CLOP	Ours
MR-T1	0.09 ±0.02	0.28 ±0.04	0.19 ±0.03	0.26 ±0.02	0.21 ±0.03	0.16 ±0.06	**0.63 ±0.05**
MR-T1D	0.19 ±0.06	0.32 ±0.11	0.27 ±0.03	0.41 ±0.10	0.27 ±0.06	0.21 ±0.02	**0.60 ±0.08**
MR-T2	0.25 ±0.03	0.48 ±0.03	0.43 ±0.05	0.44 ±0.05	0.37 ±0.05	0.32 ±0.07	**0.75 ±0.07**
MR-T2D	0.27 ±0.06	0.35 ±0.03	0.32 ±0.03	0.33 ±0.03	0.27 ±0.03	0.23 ±0.04	**0.70 ±0.04**
MR-T3	0.23 ±0.02	0.51 ±0.03	0.32 ±0.04	0.48 ±0.05	0.42 ±0.04	0.35 ±0.07	**0.66 ±0.03**
Coinrun	0.75 ±0.05	0.81 ±0.03	0.76 ±0.03	0.79 ±0.03	0.69 ±0.03	0.82 ±0.05	**0.87 ±0.02**
Jumper	0.63 ±0.07	0.61 ±0.06	0.66 ±0.04	0.67 ±0.03	0.63 ±0.05	0.68 ±0.02	**0.72 ±0.04**
Ninja	0.65 ±0.06	0.69 ±0.02	0.72 ±0.02	0.68 ±0.02	0.67 ±0.01	0.67 ±0.02	**0.79 ±0.02**
Leaper	0.48 ±0.07	0.52 ±0.04	0.47 ±0.03	0.46 ±0.01	0.48 ±0.04	0.51 ±0.07	**0.59 ±0.05**

For each of the task above, we collect its human demonstration dataset by ourselves. For each demonstration trajectory, we randomly setup the initial position of the objects, target region, and the robot. Note that the demonstration dataset provided by the original MAGICAL benchmark uses a fixed initial position setup. However, we find that this setup is too strict for structural generalization, if no other dataset or pretraining tasks present to provide prior knowledge. For MR-T1, we collect 50 trajectories. For each of the other tasks, we collect 100 trajectories. The collection of all these trajectories takes 2 hours. We also study the outcome of using a different number of trajectories in the later analysis part.

ProcGen The ProcGen benchmark is an arcade-game based benchmark. These arcade games involve interactions between many semantic objects including the player, monsters (or traps), bonuses, and tools. Though it is designed to test the generalization ability of RL agents, we use it to test the structural generalization of imitation learning here. We use four environments: Coinrun, Jumper, Ninja, and Leaper. We follow the 'easy' generalization evaluation protocol used in previous works. We first train an PPO agent (Schulman et al., 2017) to collect demonstrations in the first 200 levels of ProcGen and use these demonstrations to the imitation learning model. We use 64 expert trajectories in the experiment. Then for the evaluation, we test the imitation learning models in all the levels. We remove the background of the game throughout training and testing, since this requires observational generalization.

5.2 BASELINES

For the vanilla BC policy, we train an IMPALA (Espeholt et al., 2018) policy, whose encoder is a residual convolutional neural network. We also try vision-transformer (Dosovitskiy et al., 2021) and relational network (Santoro et al., 2017) which have relational biases, but we find that they do not work well here and not report their results. Then, we implement the following baselines for comparison. (1) **Dropout**. Dropout (Srivastava et al., 2014) is a widely-used regularization method in deep learning. Many works also find it useful for improving the performance of imitation learning. (2). **Cutout** Cutout (DeVries & Taylor, 2017) is a data augmentation method. During training, it randomly erase part of the input image. (3). **MixReg** MixReg (Wang et al., 2020) is a data augmentation method. It generates interpolated, synthetic training data based on the original training dataset. (4). **OREO** OREO (Park et al., 2021) is an object-aware data augmentation method. It randomly drop the features of certain objects. (5) **CLOP** (Bertoin & Rachelson, 2022) CLOP is a locality-aware data augmentation method. It randomly shuffles the feature map of the policy network in a small, local region.

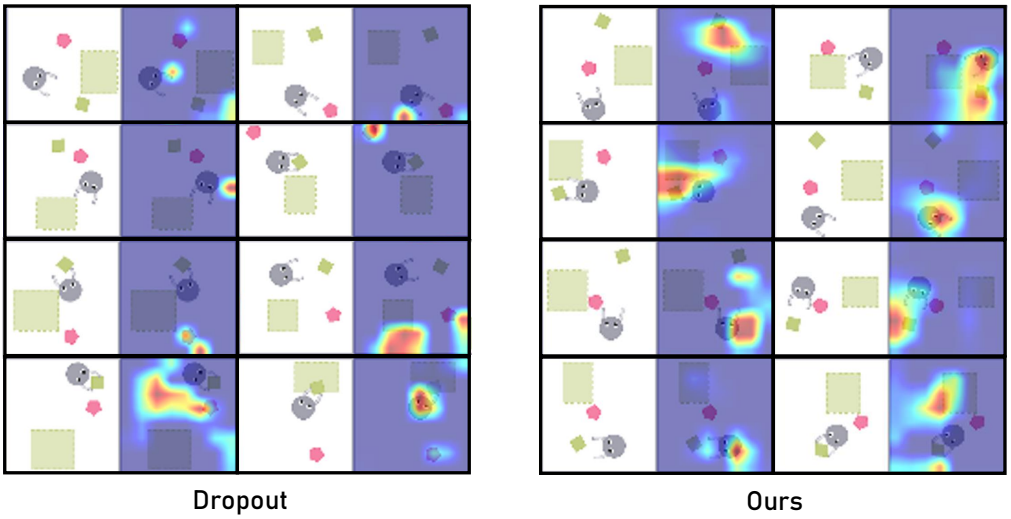

Figure 4: The GradCAM++ importance heatmap of the dropout model (left) and our model (right) on the MatchRegion-Target-1-Distract task. The red region indicates the most important region, while the dark blue indicates the least important region. The results suggest that the dropout model attends to distractor object and is not robust. In contrast, our model is able to attend to correct objects.

5.3 Results

MAGICAL The result on MAGICAL is shown in the Table 1. The performance is defined by the success rate of the trained policy, which is the number of target objects that are successfully transferred to the target region, divided by the total number of target objects. We observe that our method is able to achieve the state-of-the-art result and outperform the baselines by a large margin. Concretely, it improves the success rate by about 30%. We also notice that the improvement becomes a little stronger as the number of objects increase, when inferring correct actions become more challenging. Besides, we find that most of the previous regularization does increase the success rate of the vanilla version and can reach similar results. This result show that they may solve some common issues in the generalization problem. However, their performance gap from our method suggest that we tackle a different issue here, which is overfitting to absolute position.

ProcGen The result on ProcGen is shown in the Table 2. The performance is calculated as the normalized agent's reward in the test environment (with respect to the random agent's and expert's performance). Though we observe some improvement, the performance gain is smaller in this case compared to that of MAGICAL. We hypothesize that this is because the decision-making ProcGen is highly dependent on the local image patches as is suggested by CLOP. In this case, the BC model does not need to perform long-range reasoning across objects and suffers less from the risk of overfitting to absolute positional information. Our result here also suggests that we need task-specific inductive biases so as to achieve good generalization performance.

5.4 Analysis

Qualitative Results To understand whether our method learns more robust features, we use the GradCAM++ to visualize the learned model. For simplicity, we show the result on the MatchReigion-Target-1-Distract task. We compare the result of our model to the model trained with dropout here (Figure 4). We notice that the dropout model tends to focus on the red distractor object rather than the correct, target object. In contrast, our model is able to focus on the right objective. Even when the distance between the agent and the object is long, it can attend to the agent the object simultaneously. The visualization results suggest that our regularizer indeed leads to robust relational features even when the vision network IMPALA does not has a explicit relational inductive bias. This accounts for the improvement of generalization.

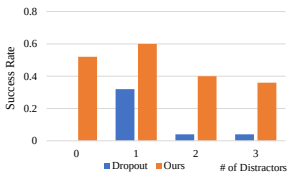

Figure 5: The generalization performance to different number of distractors on MR-T1D.

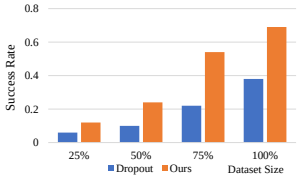

Figure 6: The variation of performance on MAGICAL using the datasets of different sizes.

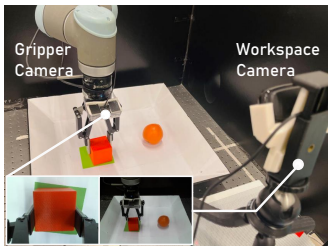

Figure 7: The setup of the real-world robot manipulation experiment.

Unseen Number of Distractors A robust model should base its decision on robust relational information. As a result, for the MAGICAL tasks, it should be able to ignore the distractor and generalize to unseen number of distractors. Therefore, we test whether our model trained on MR-T1D (where only one distractor presents) can generalize MR-T1D with unseen number of distractors (e.g. 0, 2, 3). We also compare the results with the dropout model as previous results suggest that it is a strong baseline. The result is shown in the Figure 5. We find that our model is able generalize to the case of 0, 2, 3, though the performance is lower than the case of 1 (training scenario). In contrast, the dropout model fails on these unseen cases totally. This also echoes with our qualitative analysis results.

Number of Demonstrations We also study whether the proposed method works when the amount of expert demonstrations is limited. For this purpose, we test our method on the MAGICAL with $25\%, 50\%, 75\%$ of expert demonstrations. We show the averaged performance in the Figure 6. We find that our method can achieve consistent improvement, though the performance decreases as the dataset becomes smaller. This result suggests that we still require a certain amount of diverse data to achieve structural generalization.

5.5 Real-World Experiments

Finally, we test whether our method scales to the real world manipulation problem. We extend the MR-T1D to a UR10 robot arm with a Robotiq parallel-jaw gripper (Figure 7). As is suggested by Hsu et al. (2022), we use a gripper camera and a workspace camera to provide observation. For the BC model, we use two separate IMPALA encoders to process each image, concatenate their output features, and fed them into an MLP. We use the proposed regularizer to regularize the workspace branch. We collect 75 human demonstrations for training. We compare our method to dropout with different number of distract objects. The result is shown in Table 2. Our method also achieves a large improvement in this problem.

Table 2: The success rate of the real world experiments. Our method is also effective here.

Method	Dropout	Ours
0 Dis. Obj	35%	**55%**
1 Dis. Obj	35%	**60%**
2 Dis. Obj	20%	**50%**
3 Dis. Obj	10%	**45%**

6 Conclusion

In this paper, we defined and studied the structural generalization problem of imitation learning. To solve this problem, we proposed a novel position-invariant regularizer to remove the absolute positional information from the features. Through experiments on the MAGICAL and ProcGen benchmark as well as a robot manipulation system, we confirmed that previous methods do overfit to the absolute position and showed that our proposed approach can effectively solve this problem. There are many potential future works along our direction. For instance: How to combine our method with observational generalization method? Can the usage of intepretation methods (GradCAM) here be extended in other ways for more effective generalization? We believe that answering these questions can open up new possiblities in the generalization research.

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