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# Active Vision Reinforcement Learning under Limited Visual Observability

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## Abstract

In this work, we investigate Active Vision Reinforcement Learning (ActiveVision-RL), where an embodied agent simultaneously learns action policy for the task while also controlling its visual observations in partially observable environments. We denote the former as *motor policy* and the latter as *sensory policy*. For example, humans solve real world tasks by hand manipulation (motor policy) together with eye movements (sensory policy). ActiveVision-RL poses challenges on coordinating two policies given their mutual influence. We propose SUGARL, Sensorimotor Understanding Guided Active Reinforcement Learning, a framework that models motor and sensory policies separately, but jointly learns them using with an intrinsic sensorimotor reward. This learnable reward is assigned by sensorimotor reward module, incentivizes the sensory policy to select observations that are optimal to infer its own motor action, inspired by the sensorimotor stage of humans. Through a series of experiments, we show the effectiveness of our method across a range of observability conditions and its adaptability to existed RL algorithms. The sensory policies learned through our method are observed to exhibit effective active vision strategies.

## 1 Introduction

Although Reinforcement Learning (RL) has demonstrated success across challenging tasks and games in both simulated and real environments [2, 9, 11, 89, 97], the observation spaces for visual RL tasks are typically predefined to offer the most advantageous views based on prior knowledge and can not be actively adjusted by the agent itself. For instance, table-top robot manipulators often utilize a fixed overhead camera view [51]. While such fixed viewpoints can potentially stabilize the training of an image feature encoder [14], this form of perception is different from humans who actively adjust their perception system to finish the task, e.g. eye movements [24]. The absence of active visual perception poses challenges on learning in highly dynamic environments [59, 61], open-world tasks [30] and partially observable environments with occlusions, limited field-of-views, or multiple view angles [40, 83].

We study Active Reinforcement Learning (Active-RL) [102], the RL process that allows the embodied agent to actively acquire new perceptual information in contrast to the standard RL, where the new information could be reward signals [3, 23, 27, 50, 56, 62], visual observations [32, 33], and other forms. Specifically, we are interested in visual Active-RL tasks, i.e. ActiveVision-RL, that an agent controls its own views of visual observation, in an environment with limited visual observability [33]. Therefore, the goal of ActiveVision-RL is to learn two policies that still maximize the task return: the *motor policy* to finish the task and the *sensory policy* to control the observation.

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Our project page, code, and library are available at this link

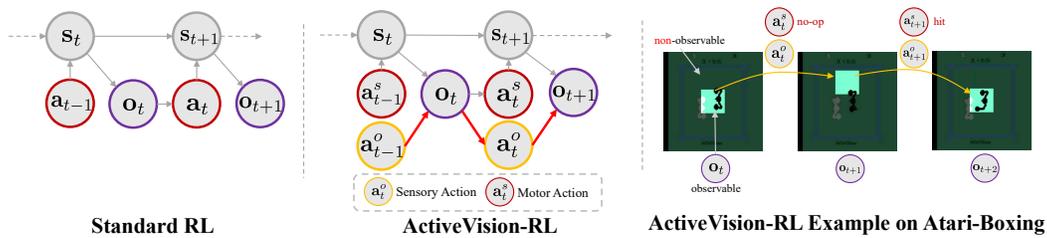


Figure 1: ActiveVision-RL with limited visual observability in comparison with standard RL, with exemplary process in Atari game *Boxing*. Red arrows stand for additional relationships considered in ActiveVision-RL. In the example on the right, the highlighted regions are the actual observations visible to the agent at each step. The rest of the pixels are not visible to the agent.

ActiveVision-RL tasks present a considerable challenge due to the coordination between motor and sensory policies, given their mutual influence [102]. The motor policy requires clear visual observation for decision-making, while the sensory policy should adapt accordingly to the motor action. Depending on the sensory policy, transitioning to a new view could either aid or hinder the motor policy learning [14, 40, 102]. One notable impediment is the perceptual aliasing mentioned by Whitehead and Ballard [102]. An optimal strategy for sensory policy should be incorporating crucial visual information while eliminating any distractions. In the real world, humans disentangle their sensory actions, such as eye movements, from their motor actions, such as manipulation, and subsequently learn to coordinate them [59, 61]. Despite being modeled separately, these two action policies and the coordination can be learned jointly through the interaction during sensorimotor stage [25, 71, 72, 103].

Taking inspiration from human capabilities, we propose SUGARL: Sensorimotor Understanding Guided Active Reinforcement Learning, an Active-RL framework designed to jointly learn sensory and motor policies by maximizing extra intrinsic sensorimotor reward together with environmental reward. We model the ActiveVision-RL agent with separate sensory and motor policies by extending existing RL algorithms with two policy/value branches. Inspired by sensorimotor stage [71, 72, 103], we use the intrinsic sensorimotor reward to guide the joint learning of two policies, imposing penalties on the agent for selecting sub-optimal observations. We use a learned sensorimotor reward module to assign the intrinsic reward. The module is trained using inverse dynamics prediction task [52, 95], with the same experiences as policy learning without additional data or pre-training.

In our experiments, we use modified Atari [9] and DeepMind Control suite (DMC) [97] with limited observability to comprehensively evaluate our proposed method. We also test on Robosuite tasks to demonstrate the effectiveness of active agent in 3D manipulation. Through the challenging benchmarks, we experimentally show that SUGARL is an effective and generic approach for Active-RL with minimum modification on top of existed RL algorithms. The learned sensory policy also exhibit active vision skills by analogy with humans' fixation and tracking.

## 2 Active Vision Reinforcement Learning Settings

Consider a vanilla RL setting based on a Markov Decision Process (MDP) described by  $(\mathcal{S}, \mathcal{A}, r, P, \gamma)$ , where  $\mathcal{S}$  is the state space,  $\mathcal{A}$  is the action space,  $r$  is the reward function,  $P$  describes state transition which is unknown and  $\gamma$  is the discount factor. In this work, we study ActiveVision-RL under limited visual observability, described by  $(\mathcal{S}, \mathcal{O}, \mathcal{A}^s, \mathcal{A}^o, r, P, \gamma)$ , as shown in Figure 1.  $\mathcal{O}$  is the actual partial observation space the agent perceives. In particular, we are interested in visual tasks, so each observation  $\mathbf{o}$  is an image contains partial information of an environmental state  $\mathbf{s}$ , like an image crop in 2D space or a photo from a viewpoint in 3D space. To emulate the human ability, there are two action spaces for the agent in Active-RL formulation.  $\mathcal{A}^s$  is the motor action space that causes state change  $p(\mathbf{s}'|\mathbf{s}, \mathbf{a}^s)$ .  $\mathcal{A}^o$  is the sensory action space that only changes the observation of an environmental state  $p(\mathbf{o}|\mathbf{s}, \mathbf{a}^o)$ . In this setting, the agent needs to take  $(\mathbf{a}^s, \mathbf{a}^o)$  for each step, based on observation(s) only. An example is shown in Figure 1.

Our goal is to learn the motor and sensory action policies  $(\pi^s, \pi^o)$  that still maximize the return  $\sum r_t$ . Note that the agent is never exposed to the full environmental state  $\mathbf{s}$ . Both policies are completely based on the partial observations:  $\mathbf{a}^s = \pi^s(\cdot|\mathbf{o})$ ,  $\mathbf{a}^o = \pi^o(\cdot|\mathbf{o})$ . Therefore the overall policy learning is challenging due to the limited information per step and the non-stationary observations.

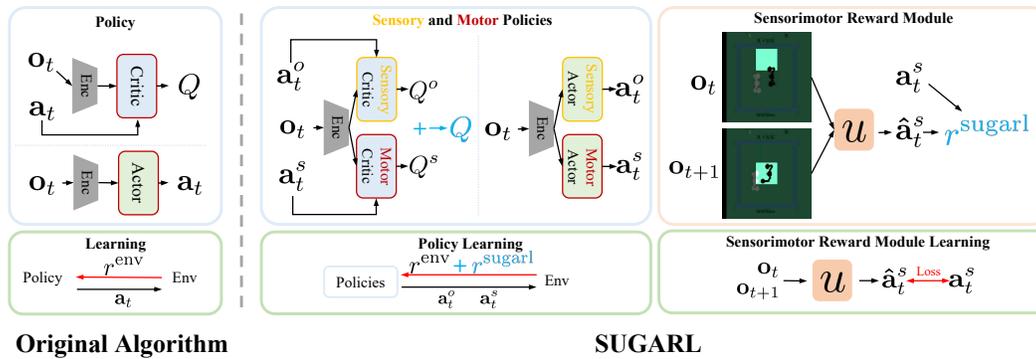


Figure 2: Overview of SUGARL and the comparison with original RL algorithm formulation. SUGARL introduces an extra sensory policy head, and jointly learns two policies together with the extra sensorimotor reward. We use the formulation of SAC [36] as an example. We introduce sensorimotor reward module to assign the reward. The reward indicates the quality of the sensory policy through the prediction task. The sensorimotor reward module is trained independently to the policies by action prediction error.

### 3 SUGARL: Sensorimotor Understanding Guided Active-RL

#### 3.1 Active-RL Algorithm with Sensorimotor Understanding

We implement Active-RL algorithms based on the normal vision-based RL algorithms with simple modifications regarding separated motor and sensory policies ( $\pi^s, \pi^o$ ), and the sensorimotor reward  $r^{\text{sugarl}}$ . We use DQN [65] and SAC [36] as examples to show the modifications are generally applicable. The example diagram of SAC is shown in Figure 2. We first introduce the policy then describe the sensorimotor reward in Section 3.2

**Network Architecture** The architectural modification is branching an additional head for sensory policy, and both policies share a visual encoder stem. For DQN [65], two heads output  $Q^s, Q^o$  for each policy respectively. This allows the algorithm to select  $\mathbf{a}^s = \arg \max_{\mathbf{a}^s} Q^s$  and  $\mathbf{a}^o = \arg \max_{\mathbf{a}^o} Q^o$  for each step. Similarly for SAC [36], the value and actor networks also have two separate heads for motor and sensory policies. The example in the form of SAC is in Figure 2.

**Joint Learning of Motor and Sensory Policies** Though two types of actions are individually selected or sampled from network outputs, we find that the joint learning of two policies benefits the whole learning [41, 111]. The joint learning here means both policies are trained using a shared reward function. Otherwise, the sensory policy usually fails to learn with intrinsic reward signal only. Below we give the formal losses for DQN and SAC.

For DQN, we take the sum of Q-values from two policies  $Q = Q^s + Q^o$  and train both heads jointly. The loss is the following where we indicate our modifications by blue:

$$\mathcal{L}_i^Q(\theta_i) = \mathbb{E}_{(\mathbf{o}_t, \mathbf{a}_t^s, \mathbf{a}_t^o) \sim \mathcal{D}} \left[ \left( y_i - \left( Q_{\theta_i}^s(\mathbf{o}_t, \mathbf{a}_t^s) + Q_{\theta_i}^o(\mathbf{o}_t, \mathbf{a}_t^o) \right) \right)^2 \right]$$

$$y_i = \mathbb{E}_{\mathbf{o}_{t+1}} \left[ r_t^{\text{env}} + \beta r_t^{\text{sugarl}} + \gamma \left( \max_{\mathbf{a}_{t+1}^s} Q_{\theta_{i-1}}^s(\mathbf{o}_{t+1}, \mathbf{a}_{t+1}^s) + \max_{\mathbf{a}_{t+1}^o} Q_{\theta_{i-1}}^o(\mathbf{o}_{t+1}, \mathbf{a}_{t+1}^o) \right) \right],$$

where  $L^Q$  is the loss for Q-networks,  $\theta$  stands for the parameters of both heads and the encoder stem,  $i$  is the iteration, and  $\mathcal{D}$  is the replay buffer.  $\beta r_t^{\text{sugarl}}$  is the extra sensorimotor reward with balancing scale which will be described in Section 3.2.

For SAC, we do the joint learning similarly. The soft-Q loss is in the similar form of above DQN which is omitted for simplicity. The soft-value loss  $L^V$  and is

$$\mathcal{L}^V(\psi) = \mathbb{E}_{\mathbf{o}_t \sim \mathcal{D}} \left[ \frac{1}{2} \left( V_{\psi}^s(\mathbf{o}_t) + V_{\psi}^o(\mathbf{o}_t) - \mathbb{E}_{\mathbf{a}_t^s \sim \pi_{\phi}^s, \mathbf{a}_t^o \sim \pi_{\phi}^o} \left[ Q_{\psi}^s(\mathbf{o}_t, \mathbf{a}_t^s) + Q_{\psi}^o(\mathbf{o}_t, \mathbf{a}_t^o) - \log \pi_{\phi}^s(\mathbf{a}_t^s | \mathbf{o}_t) - \log \pi_{\phi}^o(\mathbf{a}_t^o | \mathbf{o}_t) \right] \right)^2 \right],$$

and the actor loss  $\mathcal{L}^{\pi}$  is

$$\mathcal{L}^{\pi}(\phi) = \mathbb{E}_{\mathbf{o}_t \sim \mathcal{D}} \left[ \log \pi_{\phi}^s(\mathbf{a}_t^s | \mathbf{o}_t) + \log \pi_{\phi}^o(\mathbf{a}_t^o | \mathbf{o}_t) - Q_{\psi}^s(\mathbf{o}_t, \mathbf{a}_t^s) - Q_{\psi}^o(\mathbf{o}_t, \mathbf{a}_t^o) \right],$$

where  $\psi, \phi$  are parameters for the critic and the actor respectively, and reparameterization is omitted for clearness.

### 3.2 Sensorimotor Reward

The motor and sensory policies are jointly trained using a shared reward function, which is the combination of environmental reward and our sensorimotor reward. We first introduce the assignment of sensorimotor reward and then describe the combination of two rewards.

The sensorimotor reward is assigned by the sensorimotor reward module  $u_\xi(\cdot)$ . The module is trained to have the sensorimotor understanding, and is used to indicate the goodness of the sensory policy, tacking inspiration of human sensorimotor learning [72]. The way we obtain such reward module is similar to learning an inverse dynamics model [95]. Given a transition  $(\mathbf{o}_t, \mathbf{a}_t^s, \mathbf{o}_{t+1})$ , the module predicts the motor action  $\mathbf{a}^s$  only, based on an observation transition tuple  $(\mathbf{o}_t, \mathbf{o}_{t+1})$ . When the module is (nearly) fully trained, the higher prediction error indicates the worse quality of visual observations. For example, if the agent is absent from observations, it is hard to infer the motor action. Such sub-optimal observations also confuse agent’s motor policy. Since the sensory policy selects those visual observations, the quality of visual observations is tied to the sensory policy. As a result, we can employ the negative error of action prediction as the sensorimotor reward:

$$r_t^{\text{sugarl}} = - (1 - p(\mathbf{a}_t^s | \mathbf{o}_t, \mathbf{o}_{t+1}; u_\xi)). \quad (1)$$

This non-positive intrinsic reward penalizes the sensory policy for selecting sub-optimal views that do not contribute to the accuracy of action prediction and confuse motor policy learning. In Section 5.4 we show that naive positive rewarding does not guide the policy well. Note that the reward is less noisy when the module is fully trained. However, it is not harmful for being noisy at the early stage of training, as the noisy signal may encourage the exploration of policies. We use the sensorimotor reward though the whole learning.

The sensorimotor reward module is implemented by an independent neural network. The loss is a simple prediction error:

$$\mathcal{L}^u(\xi) = \mathbb{E}_{\mathbf{o}_t, \mathbf{o}_{t+1}, \mathbf{a}_t^s \sim \mathcal{D}} [\text{Error}(\mathbf{a}_t^s - u_\xi(\mathbf{o}_t, \mathbf{o}_{t+1}))], \quad (2)$$

where the  $\text{Error}(\cdot)$  can be a cross-entropy loss for discrete action space or L2 loss for continuous action space. Though being implemented and optimized separately, the sensorimotor reward module uses the same experience data as policy learning, with no extra data or prior knowledge introduced.

**Combining Sensorimotor Reward and Balancing** The sensorimotor reward  $r^{\text{sugarl}}$  is added densely on a per-step basis, on top of the environmental reward  $r^{\text{env}}$  in a balanced form:

$$r_t = r_t^{\text{env}} + \beta r_t^{\text{sugarl}}, \quad (3)$$

where  $\beta$  is the balance parameter varies across environments. The reward balance is very important to make both motor and sensory policies work as expected, without heavy bias towards one side [28], which will be discussed in our ablation study in Section 5.4. Following the studies in learning with intrinsic rewards and rewards of many magnitudes [20, 38, 75, 96, 99], we empirically set  $\beta = \mathbb{E}_\tau [\sum_{t=1}^T r_t^{\text{env}} / T]$ , which is the average environmental return normalized by the length of the trajectory. We get these referenced return data from the baseline agents trained on normal, fully observable environments, or from the maximum possible environmental return of one episode.

### 3.3 Persistence-of-Vision Memory

To address ActiveVision-RL more effectively, we introduce a Persistence-of-Vision Memory (PVM) to spatio-temporally combine multiple recent partial observations into one, mimicking the nature

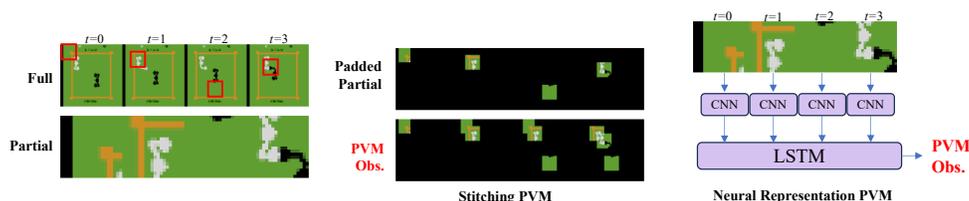


Figure 3: Examples for different instantiations of PVM with  $B = 3$ .

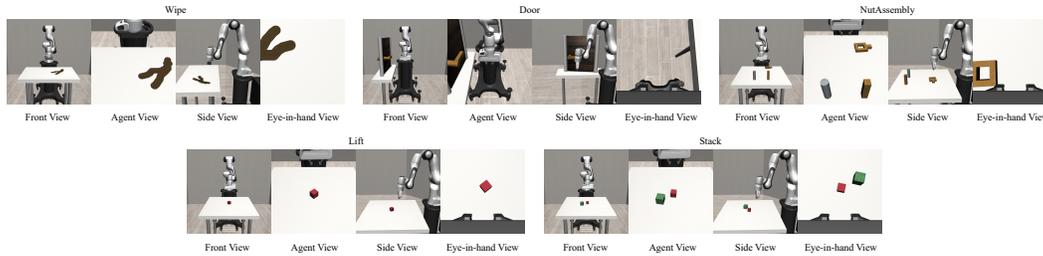


Figure 4: Five selected Robosuite tasks with examples on four hand-coded views.

of human eyes and the memory. PVM aims to expand the effective observable area, even though some visual observations may become outdated or be superseded by more recent observations. PVM stores the observations from  $B$  past steps in a buffer and combines them into a single PVM observation according to their spatial positions. This PVM observation subsequently replaces the original observation at each step:

$$\text{PVM}(\mathbf{o}_t) = f(\mathbf{o}_{t-B+1}, \dots, \mathbf{o}_t),$$

where  $f(\cdot)$  is a combination operation. In the context of ActiveVision-RL, it is reasonable to assume that the agent possesses knowledge of its focus point, as it maintains the control over the view. Therefore, the viewpoint or position information can be used. In our implementations of  $f(\cdot)$  shown in Figure 3, we show a 2D case of PVM using stitching, and a PVM using LSTM which can be used in both 2D and 3D environments. In stitching PVM, the partial observations are combined like a Jigsaw puzzle. It is worth noting that combination function  $f$  can be implemented by other pooling operations, sequence representations [15, 44, 85, 86], neural memories [37, 39, 76, 78], or neural 3D representations [74, 107], depending on the input modalities, tasks, and approaches.

## 4 Environments and Settings

### 4.1 Active-Gym: An Environment for ActiveVision-RL

We present Active-Gym, an open-sourced customized environment wrapper designed to transform RL environments into ActiveVision-RL constructs. Our library currently supports active vision agent on Robosuite [114], a robot manipulation environment in 3D, as well as Atari games [9] and the DeepMind Control Suite (DMC) [97] offering 2D active vision cases. These 2D environments were chosen due to the availability of full observations for establishing baselines and upper bounds, and the availability to manipulate observability for systematic study.

### 4.2 Robosuite Settings

**Observation Space** In the Robosuite environment, the robot controls a movable camera. The image captured by that camera is a partial observation of the 3D space.

**Action Spaces** Each step in Active-Gym requires motor and sensory actions ( $\mathbf{a}^s, \mathbf{a}^o$ ). The motor action space  $\mathcal{A}^s$  is the same as the base environment. The sensory action space  $\mathcal{A}^o$  is a 5-DoF control: relative ( $x, y, z, \text{yaw}, \text{pitch}$ ). The maximum linear and angular velocities are constrained to 0.01/step and 5 degrees/step, respectively.

### 4.3 2D Benchmark Settings

**Observation Space** In the 2D cases of Active-Gym, given a full observation  $\mathbf{O}$  with dimensions  $(H, W)$ , only a crop of it is given to the agent's input. Examples are highlighted in red boxes in Figure 5. The sensory action decides an observable area by a location  $(x, y)$ , corresponding to the top-left corner of the bounding box, and the size of the bounding box  $(h, w)$ . The pixels within the observable area becomes the foveal observation, defined as  $\mathbf{o}^f = \mathbf{o}^c = \mathbf{O}[x : x + h, y : y + w]$ . Optionally, the foveal observation can be interpolated to other resolutions  $\mathbf{o}^f = \text{Interp}(\mathbf{o}^c; (h, w) \rightarrow (r_h^f, r_w^f))$ , where  $(r_h^f, r_w^f)$  is the foveal resolution. This design allows for flexibility in altering the observable area size while keeping the effective foveal resolution constant. Typically we set  $(r_h^f, r_w^f) = (h, w)$  and fixed them during a task. The peripheral observation can be optionally provided as well, obtained by interpolating the non-foveal part  $\mathbf{o}^p = \text{Interp}(\mathbf{O} \setminus \mathbf{o}^c; (H, W) \rightarrow (r_h^p, r_w^p))$ , where  $(r_h^p, r_w^p)$  is the peripheral resolution. The examples are at the even columns of Figure 5. If the peripheral observation is not provided,  $\mathbf{o}^p = 0$ .

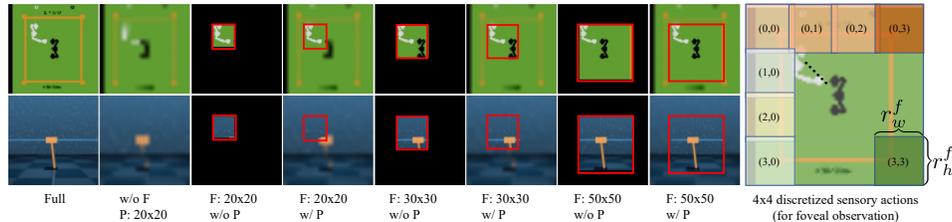


Figure 5: Left: observations from Active-Gym with different foveal resolutions (F) and peripheral settings (P) in Atari and DMC. The red bounding boxes show the observable area (foveal) for clarity. Right: 4x4 discrete sensory action options in our experiments.

Table 1: Results on Robosuite. We report the IQM of raw rewards from 30 evaluations. Highlighted task names are harder tasks. **Bold** numbers are the best scores of each task and underscored numbers are the second best.

Approach	Wipe	Door	NutAssemblySquare	Lift	Stack
SUGARL-DrQ (Stacking PVM)	56.0	274.8	78.0	79.2	12.7
SUGARL-DrQ (LSTM PVM)	<u>58.5</u>	<u>266.9</u>	<b>108.6</b>	88.8	31.5
SUGARL-DrQ (3D Transformation+LSTM PVM)	<b>74.1</b>	<b>291.0</b>	65.2	87.5	<u>32.4</u>
SUGARL-DrQ w/o Joint Learning	43.6	175.4	58.0	107.2	12.0
SUGARL-DrQ w/o PVM	52.8	243.3	37.9	55.6	7.7
Single Policy	12.4	22.8	8.42	10.7	0.53
DrQ w/ Object Detection (DETR)	15.2	43.1	54.8	15.4	7.5
DrQ w/ End-to-End Attention	14.2	141.4	28.5	33.0	13.6
Eye-in-hand View (hand-coded, moving camera)	16.1	114.6	<u>102.9</u>	<b>233.9</b>	<b>73.0</b>
Front View (hand-coded, fixed camera)	49.4	240.6	39.6	69.0	13.8
Agent View (hand-coded, fixed camera)	12.7	190.3	49.9	<u>122.6</u>	14.7
Side View (hand-coded, fixed camera)	25.9	136.2	34.5	56.6	12.8

**Action Spaces** The sensory action space  $\mathcal{A}^o$  includes all the possible (pixel) locations on the full observation, but can be further formulated to either continuous or discrete spaces according to specific task designs. In our experiments, we simplify the space by a 4x4 discrete grid-like anchors for  $(x, y)$  (Figure 5 right). Each anchor corresponds to the top-left corner of the observable area. The sensory policy chooses to place the observable area among one of 16 anchors (**absolute** control), or moves it from one to the four neighbor locations (**relative** control).

#### 4.4 Learning Settings

In our study, we primarily use DQN [65] and SAC [36] as the backbone algorithms of SUGARL to address tasks with discrete action spaces (Atari), and use DrQv2 [108] for continuous action spaces (DMC and Robosuite). All the visual encoders are standardized as the convolutional networks utilized in DQN [65]. To keep the network same, we resize all inputs to 84x84. For the sensorimotor understanding model, we employ the similar visual encoder architecture with a linear head to predict  $\mathbf{a}_t^s$ . Each agent is trained with one million transitions for each of the 26 Atari games, or trained with 0.1 million transitions for each of the 6 DMC tasks and 5 Robosuite tasks. The 26 games are selected following Atari-100k benchmark [47]. We report the results using Interquartile Mean (IQM), with the scores normalized by the IQM of the base DQN agent under full observation (except Robosuite), averaged across five seeds (three for Robosuite) and all games/tasks per benchmark. Details on architectures and hyperparameters can be found in the Appendix.

## 5 Results

### 5.1 Robosuite Results

We selected five of available tasks in Robosuite [114], namely block lifting (Lift), block stacking (Stack), nut assembling (NutAssemblySquare), door opening (Door), wiping the table (Wipe). The first two are easier compared to the later three. Example observations are available in Figure 4. We compare against a straightforward baseline that a single policy is learned to govern both motor and sensory actions. We also compare to baselines including RL with object detection (a replication of Cheng et al. [17]), learned attention [93], and standard RL with hand-coded views. Results are in 1. We confirm that our SUGARL works outperforms baselines all the time, and also outperforms

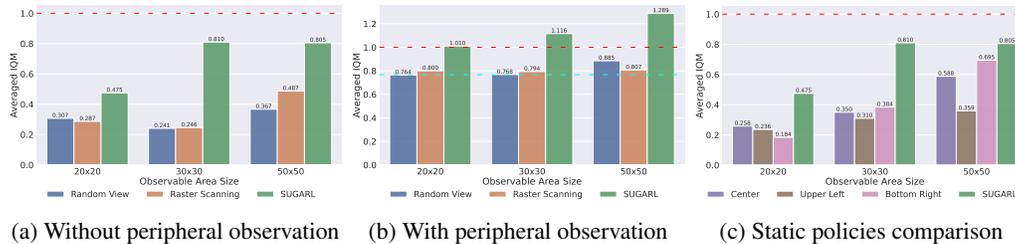


Figure 6: Results with different observation size and peripheral observation settings. The green bars are results from SUGARL. The red dashed lines stand for the DQN baseline trained on full observations using the same amount of data. We compare SUGARL against two dynamic views: Random View and Raster Scanning, and three static view baselines. In (b) with peripheral observation, we compare a baseline using peripheral observation only indicated by the cyan line.

the hand-coded views most of the time. Specifically, for the harder tasks including Wipe, Door, and NutAssemblySquare, SUGARL gets the best scores.

**Designs of PVM** We compare different instantiations of proposed PVMs including: Stacking: naively stacking multiple frames; LSTM: Each image is first encoded by CNN and fed into LSTM; 3D Transformation + LSTM: we use camera parameters to align pixels from different images to the current camera frame. Then an LSTM encodes the images after going through CNN. We find that 3D Transformation + LSTM works the best, because it tackles spatial aligning and temporal merging together. LSTM also works well in general.

## 5.2 2D Benchmark Results

We evaluate the policy learning on Atari under two primary visual settings: **with** and **without peripheral observation**. In each visual setting we explore three sizes of observable area (set equivalent to foveal resolution): **20x20**, **30x30**, and **50x50**. In with peripheral observation setting, the peripheral resolution is set to 20x20 for all tasks. We use DQN [65]-based SUGARL (SUGARL-DQN) and compare it against two variants by replacing the learnable sensory policy in SUGARL with: **Random View** and **Raster Scanning**. Random View always uniformly samples from all possible crops. Raster Scanning uses a pre-designed sensory policy that chooses observable areas from left to right and top to down sequentially. Raster Scanning yields relatively stable observation patterns and provides maximum information under PVM. We also provide a DQN baseline trained on full observations (84x84) as a soft oracle. In with peripheral observation settings, another baseline trained on peripheral observation only (20x20) is compared as a soft lower bound.

In Figure 6a and 6b, we find that SUGARL performs the best in all settings, showing that SUGARL learns effective sensory and motor policies jointly. More importantly, SUGARL with peripheral observation achieves higher overall scores (+0.01~0.2) than the full observation baselines. In details, SUGARL gains higher scores than the full observation baseline in 13 out of 26 games with 50x50 foveal resolution (details are available in the Appendix). This finding suggests the untapped potential of ActiveVision-RL agents which leverage partial observations better than full observations. By actively selecting views, the agent can filter out extraneous information and concentrate on task-centric information.

**Compare against Static Sensory Policies** We also examine baselines with static sensory policies, which consistently select one region to observe throughout all steps. The advantage of this type baseline lies in the stability of observation. We select 3 regions: **Center**, **Upper Left**, and **Bottom Right**, and compare them against SUGARL in environment w/o peripheral observation. As shown in Figure 6c, we observe that SUGARL still surpasses all three static policies. The performance gaps between SUGARL and Center and Bottom Right are relatively small when the observation size is larger (50x50), as the most valuable information is typically found at these locations in Atari

Table 2: Evaluation results on different conditions and algorithm backbones

(a) Action modeling				(b) Train more steps					(c) SUGARL with SAC				(d) Different PVMs			
Model	20	30	50	Steps	Model	20	30	50	Model	20	30	50	Model	20	30	50
SUGARL (abs)	<b>0.475</b>	<b>0.810</b>	0.805	1M	SUGARL	<b>0.475</b>	<b>0.810</b>	<b>0.805</b>	SUGARL	<b>0.424</b>	<b>0.730</b>	<b>0.785</b>	Stitching PVM	<b>0.475</b>	<b>0.815</b>	<b>0.810</b>
SUGARL (rel)	0.367	0.745	<b>0.945</b>		Single Policy	0.132	0.222	0.171	SUGARL w/o $p^{*}$ -steparl	0.300	0.307	0.504	LSTM PVM	0.397	0.448	0.470
				5M	SUGARL	<b>1.170</b>	<b>1.121</b>	<b>1.553</b>	SAC-raster scanning	0.117	0.195	0.136				
Single Policy	0.132	0.222	0.171		Single Policy	0.332	0.640	1.145	SAC-random view	0.155	0.104	0.134				

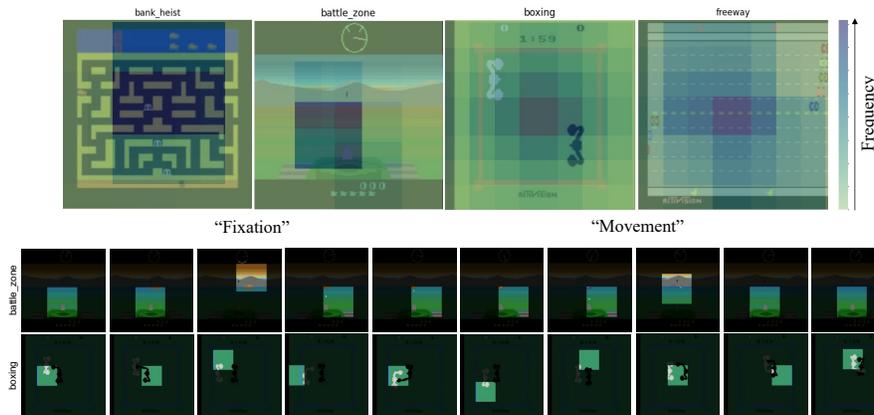


Figure 7: Examples of learned sensory policies from SUGARL-DQN. Top: frequency heat maps of pixels being observed. Bottom: sequences of observations showing fixation-like and tracking-like behaviors. More videos are available at this link

environments. Static observation is therefore quite beneficial for decision-making. However, as the observation size decreases, an active policy becomes essential for identifying optimal observations, leading SUGARL to outperform others by a significant margin.

**Sensory-Motor Action Spaces Modeling** SUGARL models the sensory and motor action spaces separately inspired by the human abilities. An alternative approach is jointly modeling two action spaces  $\mathcal{A} = \mathcal{A}^s \times \mathcal{A}^o$  and learning one single action policy, with environmental reward only (referred as **Single Policy**). We compare Single Policy and display the results in Table 2a, which reveal that modeling one large action space fails to learn the policy properly due to the expanded action space. Additionally, we examine two types of sensory action spaces: **absolute** (abs) and **relative** (rel). Absolute modeling allows the view to jump across the entire space while relative modeling restricts the view to moving only to the neighboring options at each step. Results in Table 2a indicate that the absolute modeling performs better in smaller observable regions, as it can select the desired view more quickly than relative modeling. In contrast, relative modeling demonstrates better performance in larger observable region setting as it produces more stable observations across steps.

**Training More Steps** We subsequently explore SUGARL performance when trained with more environmental steps, comparing outcomes between 1M and 5M steps. Results in Table 2b confirm that SUGARL continuous to improve with more steps and consistently outperforms the single policy baseline, suggesting that it does not merely stagnate at a trivial policy. However, due to the challenges posed by limited observability, the learning still proceeds slower than for the agent with full observations, which achieves the score 4.106 at 5M steps.

**Generalization of SUGARL** We apply SUGARL to Soft Actor-Critic (SAC) [36] and evaluate its performance on environments without peripheral observation. As before, we compare it with Random View, Raster Scanning, and SUGARL without intrinsic reward. According to Table 2c, we find that SUGARL-SAC outperforms the naive version without the guidance of  $r^{\text{sugarl}}$ , further emphasizing the significance of our method. Moreover, SUGARL-SAC also surpasses the random view and raster scanning policies. However, when employing max-entropy-based methods like SAC, it is necessary to reduce the weight of the entropy term to ensure consistency in the sensory policy. We will further discuss it in Section 5.3 based on the analysis of the learned sensory policy behavior.

**DMC Tasks** We also evaluate SUGARL on DMC [97] tasks based on DrQ [108], an improved version of DDPG [100]. We use six environments in DMC [97]: *ball\_in\_cup-catch*, *cartpole-swingup*, *cheetah-run*, *dog-fetch*, *fish-swim*, and *walker-walk*. Three foveal observation resolutions (20x20, 30x30, and 50x50) without peripheral observation are explored. We use relative control for sensory action and decide the discrete sensory options by thresholding the continuous output. We compare our approach with baselines with joint modeling of sensory and motor action spaces (Single Policy), Raster Scanning, and Random View. Results are shown in Table 3. SUGARL outperforms all baselines in three foveal settings in DMC, showing it is also applicable to continuous control tasks.

Table 3: SUGARL on DMC

Model	20	30	50
SUGARL-DrQ	<b>0.686</b>	<b>0.717</b>	<b>1.052</b>
DrQ-Single Policy	0.540	0.570	0.776
DrQ-Raster Scanning	0.609	0.566	0.913
DrQ-Random View	0.569	0.591	0.768
SUGARL-DrQ w/o PVM	0.672	0.620	0.930
SUGARL w/o Joint Learning	0.377	0.446	0.355

### 5.3 Sensory Policy Analysis

**Sensory Policy Patterns** In Figure 7, we present examples of learned sensory policies from SUGARL-DQN in four Atari games, in settings w/o peripheral observations. These policies are visualized as heat maps based on the frequency of observed pixels. We discover that the sensory policies learn both **fixation** and **movement** (similar to tracking) behaviours [12, 110] depending on the specific task requirements. In the first two examples, the sensory policy tends to concentrate on fixed regions. In *battle\_zone*, the policy learns to focus on the regions where enemies appear and the fixed front sight needed for accurate firing. By contrast, in highly dynamic environments like *boxing* and *freeway*, the sensory policies tend to observe broader areas in order to get timely observations. Though not being a perfect tracker, the sensory policy learns to track the agent or the object of interest in these two environments, demonstrating the learned capability akin to humans’ Smooth Pursuit Movements. Recorded videos for entire episodes are available at our project page.

**Sensory Policy Distribution** We quantitatively assess the distributions of learned sensory policies. There are 16 sensory actions, i.e. the observable area options in our setup (Figure 5). We compare the distributions against uniform distribution using KL-divergence, across 26 games x 10 eval runs x 5 seeds. The resulting histogram are shown in Figure 8. We observe that the learned policies consistently deviate from the uniform distribution, suggesting that sensory policies prefer specific regions in general. The high peak at the high KL end supports the “fixation” behavior identified in the previous analysis. As the observation size increases, the divergence distribution shifts towards smaller KL end, while remaining  $> 0.5$  for all policies. This trend indicates that with larger observable sizes, the policy does not need to adjust its attention frequently, corroborating the benefit of using relative control shown in Table 2a.

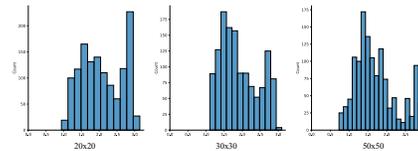


Figure 8: KL divergence distributions of learned sensory policies.

**Pitfalls on Max-Entropy Based Methods** In the previous analysis, we both qualitatively and quantitatively demonstrate that sensory policies are not uniformly dispersed across the entire sensory action space. This observation implies that *sensory* policy should exercise caution when adopting the max-entropy-based methods. We conduct an experiment on varying the usage of  $\alpha$ , the entropy coefficient in SAC in all three foveal observation size settings. Results in Table 4 show that simply disabling autotune and setting a small value to the sensory policy’s  $\alpha$  improves. This finding tells that max-entropy may not be a suitable assumption in modeling sensory policies.

Table 4: Varying  $\alpha$  of SUGARL-SAC.

Model	20	30	50
autotune $\alpha$	0.271	0.358	0.444
fixed- $\alpha = 0.2$	<b>0.424</b>	<b>0.730</b>	<b>0.785</b>

### 5.4 Ablation Studies

We conduct ablation studies in the setting without peripheral observation and with 50x50 observation size. Five crucial design components are investigated to validate their effectiveness by incrementally adding or removing them from the full model. The results are presented in Table 5. From the results, we demonstrate the importance of *penalizing* the agent for inaccurate self-understanding predictions rather than rewarding accurate predictions ( $r^{\text{sugarl}}(\text{positive}) \rightarrow r^{\text{sugarl}}(\text{negative})$ ). By imposing penalties, the maximum return is bounded by the original maximum possible return per episode, allowing motor and sensory policies to better coordinate each other and achieve optimal task performance. *Reward balance* significantly improves the policy, indicating its effectiveness in coordinating two policies as well. PVM also considerably enhances the algorithm by increasing the effective observable area as expected.

Table 5: Ablation study results based on DQN 50x50 foveal res w/o peripheral observation. The blank fields means there are no such modifications for that model.

Model	$r^{\text{sugarl}}$	Joint Learning	PVM	Reward Balance ( $\beta$ )	IQM
Random View			✓		0.367
SUGARL = {	Base RL algorithm				-
	+Naive positive intrinsic reward	positive			0.281
	+Joint learning	positive	✓		0.322
	Positive $\rightarrow$ negative $r^{\text{sugarl}}$	negative	✓		0.360
	+PVM	negative	✓	✓	0.423
+Reward Balance	negative	✓	✓	✓	<b>0.805</b>
SUGARL w/o $r^{\text{sugarl}}$		✓	✓		0.421
SUGARL w/o $r^{\text{sugarl}}$ and w/o PVM		✓			0.231

## 6 Related Work

**Active Learning** is the concept that an agent decides which data are taken into its learning and may ask for external information in comparison to fitting a fixed data distribution [1, 6, 10, 21, 22, 31, 46, 49, 55, 57, 60, 64, 66, 73, 81, 88, 90, 101, 105, 113]. **Active Vision** focuses on continuously acquiring new visual observations that is helpful for the vision task like object classification, recognition and detection [4, 5, 7, 8, 18, 28, 29, 48, 63, 98, 106, 109], segmentation [13, 58, 70], and action recognition [45]. The active vision is usually investigated under a robot vision scenario that a robot moves around in a scene. However, the policy is usually not required to accomplish a task with physical interactions such as manipulating objects compared to reinforcement learning.

**Active Reinforcement Learning** (Active-RL), at a high level, is that the agent is allowed to actively gather new perceptual information of interest simultaneously through an RL task, which can also be called active perception [102]. The extra perceptual information could be reward signal [3, 23, 27, 50, 56, 62], visual observations from new viewpoints [33, 54, 67, 87], other input modalities [16], and language instructions [19, 68, 69, 94]. Though these work may not explicitly use the term Active-RL, we find that they can be uniformly organized in the general Active-RL formulation and we coin the term here. In our work, we study the ActiveVision-RL task in a limited visual observability environment, where at each step the agent is only able to partially observe the environment. The agent should actively seek the optimal observation at each step. Therefore, our setting is more close to [32, 33] and Active Vision problems, unlike research incorporating attention-like inductive bias given a full observation [34, 42, 43, 79, 91, 93, 104]. The ActiveVision-RL agent must learn an observation selection policy, called sensory policy, to effectively choose the optimal partial observation for executing the task-specific policy (motor policy). The unique challenge for ActiveVision-RL is the coordination between sensory and motor policies given their mutual influence. In recent works, the sensory policy can be either trained in the task-agnostic way [33] with enormous exploration data, or trained jointly with the task [32] with naive environmental reward only. In this work we investigate the joint learning case because of the high cost and availability concern of pre-training tasks [33].

**Robot Learning with View Changes** Viewpoint changes and gaps in visual observations are the common challenges for robot learning [40, 53, 77, 84, 92, 112], especially for the embodied agents that uses its first-person view [30, 35, 80]. To address those challenges, previous works proposed to map visual observation from different viewpoints to a common representation space by contrastive encoding [26, 82, 83] or build implicit neural representations [53, 107]. In many first-person view tasks, the viewpoint control is usually modeled together with the motor action like manipulation and movement [30, 80]. In contrast, in our ActiveVision-RL setting, we explore the case where the agent can choose where to observe independently to the motor action inspired by the humans' ability.

## 7 Limitations

In this work, we assume that completely independent sensory and motor actions are present in an embodied agent. But in a real-world case, the movement of the sensors may depend on the motor actions. For example, a fixed camera attached to the end-effector of a robot manipulator, or to a mobility robot. To address the potential dependence and conflicts between two policies in this case, extensions like voting or weighing across two actions to decide the final action may be required. The proposed algorithm also assumes a chance to adjust viewpoints at every step. This could be challenging for applications where the operational or latency costs for adjusting the sensors are high like remote control. To resolve this, additional penalties on sensory action and larger memorization capability are potentially needed. Last, the intrinsic reward currently only considers the accuracy of agent-centric prediction. Other incentives like gathering novel information or prediction accuracy over other objects in the environment can be further explored.

## 8 Conclusion

We present SUGARL, a framework based on existed RL algorithms to jointly learn sensory and motor policies through the ActiveVision-RL task. In SUGARL, an intrinsic reward determined by sensorimotor understanding effectively guides the learning of two policies. Our framework is validated in both 3D and 2D benchmarks with different visual observability settings. Through the analysis on the learned sensory policy, it shows impressive active vision skills by analogy with human's fixation and tracking that benefit the overall policy learning. Our work paves the initial way towards reinforcement learning using active agents for open-world tasks.

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## References

- [1] S. Agarwal, H. Arora, S. Anand, and C. Arora. Contextual diversity for active learning. In *Computer Vision–ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part XVI 16*, pages 137–153. Springer, 2020.
- [2] I. Akkaya, M. Andrychowicz, M. Chociej, M. Litwin, B. McGrew, A. Petron, A. Paino, M. Plappert, G. Powell, R. Ribas, et al. Solving rubik’s cube with a robot hand. *arXiv preprint arXiv:1910.07113*, 2019.
- [3] R. Akrou, M. Schoenauer, and M. Sebag. April: Active preference learning-based reinforcement learning. In *Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2012, Bristol, UK, September 24–28, 2012. Proceedings, Part II 23*, pages 116–131. Springer, 2012.
- [4] A. Andreopoulos and J. K. Tsotsos. A theory of active object localization. In *2009 IEEE 12th International Conference on Computer Vision*, pages 903–910. IEEE, 2009.
- [5] A. Andreopoulos and J. K. Tsotsos. A computational learning theory of active object recognition under uncertainty. *International journal of computer vision*, 101:95–142, 2013.
- [6] J. T. Ash, C. Zhang, A. Krishnamurthy, J. Langford, and A. Agarwal. Deep batch active learning by diverse, uncertain gradient lower bounds. In *International Conference on Learning Representations*, 2020.
- [7] N. Atanasov, B. Sankaran, J. Le Ny, G. J. Pappas, and K. Daniilidis. Nonmyopic view planning for active object classification and pose estimation. *IEEE Transactions on Robotics*, 30(5): 1078–1090, 2014.
- [8] R. Bajcsy, Y. Aloimonos, and J. K. Tsotsos. Revisiting active perception. *Autonomous Robots*, 42:177–196, 2018.
- [9] M. G. Bellemare, Y. Naddaf, J. Veness, and M. Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47: 253–279, jun 2013.
- [10] W. H. Beluch, T. Genewein, A. Nürnberger, and J. M. Köhler. The power of ensembles for active learning in image classification. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 9368–9377, 2018.
- [11] C. Berner, G. Brockman, B. Chan, V. Cheung, P. Debiak, C. Dennison, D. Farhi, Q. Fischer, S. Hashme, C. Hesse, et al. Dota 2 with large scale deep reinforcement learning. *arXiv preprint arXiv:1912.06680*, 2019.
- [12] A. Borji and L. Itti. State-of-the-art in visual attention modeling. *IEEE transactions on pattern analysis and machine intelligence*, 35(1):185–207, 2012.
- [13] A. Casanova, P. O. Pinheiro, N. Rostamzadeh, and C. J. Pal. Reinforced active learning for image segmentation. *arXiv preprint arXiv:2002.06583*, 2020.
- [14] E. Cetin, P. J. Ball, S. Roberts, and O. Celiktutan. Stabilizing off-policy deep reinforcement learning from pixels. In *International Conference on Machine Learning*, pages 2784–2810. PMLR, 2022.
- [15] L. Chen, K. Lu, A. Rajeswaran, K. Lee, A. Grover, M. Laskin, P. Abbeel, A. Srinivas, and I. Mordatch. Decision transformer: Reinforcement learning via sequence modeling. In *Advances in Neural Information Processing Systems (NeurIPS)*, Dec. 2021.

- [16] S. Chen, H. Cao, Q. Ouyang, X. Wu, and Q. Qian. Aids: An active learning method for multi-source materials data screening and materials design. *Materials & Design*, 223:111092, 2022. ISSN 0264-1275.
- [17] R. Cheng, A. Agarwal, and K. Fragkiadaki. Reinforcement learning of active vision for manipulating objects under occlusions. In *Conference on Robot Learning*, pages 422–431. PMLR, 2018.
- [18] R. Cheng, Z. Wang, and K. Fragkiadaki. Geometry-aware recurrent neural networks for active visual recognition. *Advances in Neural Information Processing Systems*, 31, 2018.
- [19] T.-C. Chi, M. Shen, M. Eric, S. Kim, and D. Hakkani-tur. Just ask: An interactive learning framework for vision and language navigation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 34, pages 2459–2466, 2020.
- [20] J. Choi and S.-e. Yoon. Intrinsic motivation driven intuitive physics learning using deep reinforcement learning with intrinsic reward normalization. *arXiv preprint arXiv:1907.03116*, 2019.
- [21] J. Choi, K. M. Yi, J. Kim, J. Choo, B. Kim, J. Chang, Y. Gwon, and H. J. Chang. Vab-al: Incorporating class imbalance and difficulty with variational bayes for active learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 6749–6758, 2021.
- [22] D. A. Cohn, Z. Ghahramani, and M. I. Jordan. Active learning with statistical models. *Journal of artificial intelligence research*, 4:129–145, 1996.
- [23] C. Daniel, M. Viering, J. Metz, O. Kroemer, and J. Peters. Active reward learning. In *Robotics: Science and systems*, volume 98, 2014.
- [24] R. Dodge. Five types of eye movement in the horizontal meridian plane of the field of regard. *American journal of physiology-legacy content*, 8(4):307–329, 1903.
- [25] P. W. Duncan, M. Propst, and S. G. Nelson. Reliability of the fugal-meyer assessment of sensorimotor recovery following cerebrovascular accident. *Physical therapy*, 63(10):1606–1610, 1983.
- [26] D. Dwibedi, J. Tompson, C. Lynch, and P. Sermanet. Learning actionable representations from visual observations. In *IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 1577–1584. IEEE, 2018.
- [27] A. Epshteyn, A. Vogel, and G. DeJong. Active reinforcement learning. In *Proceedings of the 25th international conference on Machine learning*, pages 296–303, 2008.
- [28] L. Fan and Y. Wu. Avoiding lingering in learning active recognition by adversarial disturbance. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, pages 4612–4621, January 2023.
- [29] L. Fan, P. Xiong, W. Wei, and Y. Wu. Flar: A unified prototype framework for few-sample lifelong active recognition. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*, pages 15394–15403, October 2021.
- [30] L. Fan, G. Wang, Y. Jiang, A. Mandlekar, Y. Yang, H. Zhu, A. Tang, D.-A. Huang, Y. Zhu, and A. Anandkumar. Minedojo: Building open-ended embodied agents with internet-scale knowledge. In *Advances in Neural Information Processing Systems*, volume 35, pages 18343–18362. Curran Associates, Inc., 2022.
- [31] Y. Gal, R. Islam, and Z. Ghahramani. Deep bayesian active learning with image data. In *International conference on machine learning*, pages 1183–1192. PMLR, 2017.
- [32] R. Göransson. Deep reinforcement learning with active vision on atari environments. In *Master's Thesis*. Lund University, 2022.
- [33] M. K. Grimes, J. V. Modayil, P. W. Mirowski, D. Rao, and R. Hadsell. Learning to look by self-prediction. *Transactions on Machine Learning Research*, 2023. ISSN 2835-8856.

- [34] S. S. Guo, R. Zhang, B. Liu, Y. Zhu, D. Ballard, M. Hayhoe, and P. Stone. Machine versus human attention in deep reinforcement learning tasks. *Advances in Neural Information Processing Systems*, 34:25370–25385, 2021.
- [35] W. H. Guss, B. Houghton, N. Topin, P. Wang, C. Codel, M. Veloso, and R. Salakhutdinov. MineRL: A large-scale dataset of Minecraft demonstrations. *Twenty-Eighth International Joint Conference on Artificial Intelligence*, 2019. URL <http://miner1.io>.
- [36] T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *Proceedings of the International Conference on Machine Learning (ICML)*, 2018.
- [37] M. J. Hausknecht and P. Stone. Deep recurrent q-learning for partially observable mdps. In *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*, 2015.
- [38] P. Henderson, R. Islam, P. Bachman, J. Pineau, D. Precup, and D. Meger. Deep reinforcement learning that matters. In *Proceedings of the AAAI conference on artificial intelligence*, volume 32, 2018.
- [39] S. Hochreiter and J. Schmidhuber. Long short-term memory. *Neural Computation*, 9(8): 1735–1780, 1997.
- [40] K. Hsu, M. J. Kim, R. Rafailov, J. Wu, and C. Finn. Vision-based manipulators need to also see from their hands. *arXiv preprint arXiv:2203.12677*, 2022.
- [41] W. Huang, I. Mordatch, and D. Pathak. One policy to control them all: Shared modular policies for agent-agnostic control. In *International Conference on Machine Learning*, pages 4455–4464. PMLR, 2020.
- [42] S. James and A. J. Davison. Q-attention: Enabling efficient learning for vision-based robotic manipulation. *IEEE Robotics and Automation Letters*, 7(2):1612–1619, 2022.
- [43] S. James, K. Wada, T. Laidlow, and A. J. Davison. Coarse-to-fine q-attention: Efficient learning for visual robotic manipulation via discretisation. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 13739–13748, 2022.
- [44] M. Janner, Q. Li, and S. Levine. Offline reinforcement learning as one big sequence modeling problem. In *Advances in Neural Information Processing Systems (NeurIPS)*, Dec. 2021.
- [45] D. Jayaraman and K. Grauman. Look-ahead before you leap: end-to-end active recognition by forecasting the effect of motion. In *Computer Vision—ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11–14, 2016, Proceedings, Part V 14*, pages 489–505. Springer, 2016.
- [46] A. J. Joshi, F. Porikli, and N. Papanikolopoulos. Multi-class active learning for image classification. In *2009 IEEE conference on computer vision and pattern recognition*, pages 2372–2379. IEEE, 2009.
- [47] L. Kaiser, M. Babaeizadeh, P. Milos, B. Osinski, R. H. Campbell, K. Czechowski, D. Erhan, C. Finn, P. Kozakowski, S. Levine, A. Mohiuddin, R. Sepassi, G. Tucker, and H. Michalewski. Model based reinforcement learning for atari. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26–30, 2020*. OpenReview.net, 2020.
- [48] S. Kasaei, J. Sock, L. S. Lopes, A. M. Tomé, and T.-K. Kim. Perceiving, learning, and recognizing 3d objects: An approach to cognitive service robots. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 32, 2018.
- [49] T. Kim, I. Hwang, H. Lee, H. Kim, W.-S. Choi, J. J. Lim, and B.-T. Zhang. Message passing adaptive resonance theory for online active semi-supervised learning. In *International Conference on Machine Learning*, pages 5519–5529. PMLR, 2021.
- [50] D. Krueger, J. Leike, O. Evans, and J. Salvatier. Active reinforcement learning: Observing rewards at a cost. *arXiv preprint arXiv:2011.06709*, 2020.

- [51] S. Levine, P. Pastor, A. Krizhevsky, J. Ibarz, and D. Quillen. Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection. *The International journal of robotics research*, 37(4-5):421–436, 2018.
- [52] X. Li, J. Shang, S. Das, and M. Ryoo. Does self-supervised learning really improve reinforcement learning from pixels? In *Advances in Neural Information Processing Systems*, volume 35, pages 30865–30881, 2022.
- [53] Y. Li, S. Li, V. Sitzmann, P. Agrawal, and A. Torralba. 3d neural scene representations for visuomotor control. In *Conference on Robot Learning*, pages 112–123. PMLR, 2022.
- [54] L. Liu, S. Fryc, L. Wu, T. L. Vu, G. Paul, and T. Vidal-Calleja. Active and interactive mapping with dynamic gaussian process implicit surfaces for mobile manipulators. *IEEE Robotics and Automation Letters*, 6(2):3679–3686, 2021.
- [55] Z. Liu, H. Ding, H. Zhong, W. Li, J. Dai, and C. He. Influence selection for active learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 9274–9283, 2021.
- [56] M. Lopes, F. Melo, and L. Montesano. Active learning for reward estimation in inverse reinforcement learning. In *Machine Learning and Knowledge Discovery in Databases: European Conference, ECML PKDD 2009, Bled, Slovenia, September 7-11, 2009, Proceedings, Part II 20*, pages 31–46. Springer Berlin Heidelberg, 2009.
- [57] W. Luo, A. Schwing, and R. Urtasun. Latent structured active learning. *Advances in Neural Information Processing Systems*, 26, 2013.
- [58] D. Mahapatra, B. Bozorgtabar, J.-P. Thiran, and M. Reyes. Efficient active learning for image classification and segmentation using a sample selection and conditional generative adversarial network. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 580–588. Springer, 2018.
- [59] J. S. Matthis, J. L. Yates, and M. M. Hayhoe. Gaze and the control of foot placement when walking in natural terrain. *Current Biology*, 28(8):1224–1233, 2018.
- [60] C. Mayer and R. Timofte. Adversarial sampling for active learning. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision*, pages 3071–3079, 2020.
- [61] M. K. McBeath, D. M. Shaffer, and M. K. Kaiser. How baseball outfielders determine where to run to catch fly balls. *Science*, 268(5210):569–573, 1995.
- [62] P. Ménard, O. D. Domingues, A. Jonsson, E. Kaufmann, E. Leurent, and M. Valko. Fast active learning for pure exploration in reinforcement learning. In *International Conference on Machine Learning*, pages 7599–7608. PMLR, 2021.
- [63] M. B. Mirza, R. A. Adams, C. D. Mathys, and K. J. Friston. Scene construction, visual foraging, and active inference. *Frontiers in computational neuroscience*, 10:56, 2016.
- [64] S. Mittal, M. Tatarchenko, Ö. Çiçek, and T. Brox. Parting with illusions about deep active learning. *arXiv preprint arXiv:1912.05361*, 2019.
- [65] V. Mnih, K. Kavukcuoglu, D. Silver, A. Graves, I. Antonoglou, D. Wierstra, and M. Riedmiller. Playing atari with deep reinforcement learning, 2013. arXiv:1312.5602.
- [66] P. Munjal, N. Hayat, M. Hayat, J. Sourati, and S. Khan. Towards robust and reproducible active learning using neural networks. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 223–232, 2022.
- [67] A. Narr, R. Triebel, and D. Cremers. Stream-based active learning for efficient and adaptive classification of 3d objects. In *2016 IEEE International Conference on Robotics and Automation (ICRA)*, pages 227–233. IEEE, 2016.

- [68] K. Nguyen and H. Daumé III. Help, anna! visual navigation with natural multimodal assistance via retrospective curiosity-encouraging imitation learning. In *Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP)*, pages 684–695, 2019.
- [69] K. Nguyen, D. Dey, C. Brockett, and B. Dolan. Vision-based navigation with language-based assistance via imitation learning with indirect intervention. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 12527–12537, 2019.
- [70] D. Nilsson, A. Pirinen, E. Gärtner, and C. Sminchisescu. Embodied visual active learning for semantic segmentation. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 2373–2383, 2021.
- [71] J. K. O’regan and A. Noë. A sensorimotor account of vision and visual consciousness. *Behavioral and brain sciences*, 24(5):939–973, 2001.
- [72] J. Piaget. Piaget’s theory, 1976.
- [73] R. Pinsler, J. Gordon, E. Nalisnick, and J. M. Hernández-Lobato. Bayesian batch active learning as sparse subset approximation. *Advances in neural information processing systems*, 32, 2019.
- [74] A. Pumarola, E. Corona, G. Pons-Moll, and F. Moreno-Noguer. D-nerf: Neural radiance fields for dynamic scenes. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 10318–10327, 2021.
- [75] A. Rangel and J. A. Clithero. Value normalization in decision making: theory and evidence. *Current opinion in neurobiology*, 22(6):970–981, 2012.
- [76] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning internal representations by error propagation. In J. W. Shavlik and T. G. Dietterich, editors, *Readings in Machine Learning*, pages 115–137, San Mateo, CA, 1990. Kaufmann.
- [77] M. S. Ryoo, T. J. Fuchs, L. Xia, J. K. Aggarwal, and L. Matthies. Robot-centric activity prediction from first-person videos: What will they do to me? In *Proceedings of the tenth annual ACM/IEEE international conference on human-robot interaction*, pages 295–302, 2015.
- [78] M. S. Ryoo, K. Gopalakrishnan, K. Kahatapitiya, T. Xiao, K. Rao, A. Stone, Y. Lu, J. Ibarz, and A. Arnab. Token turing machines. *arXiv preprint arXiv:2211.09119*, 2022.
- [79] S. Salter, D. Rao, M. Wulfmeier, R. Hadsell, and I. Posner. Attention-privileged reinforcement learning. In *Conference on Robot Learning*, pages 394–408. PMLR, 2021.
- [80] M. Savva, A. Kadian, O. Maksymets, Y. Zhao, E. Wijmans, B. Jain, J. Straub, J. Liu, V. Koltun, J. Malik, D. Parikh, and D. Batra. Habitat: A platform for embodied ai research. In *2019 IEEE/CVF International Conference on Computer Vision (ICCV)*. IEEE, Oct 2019.
- [81] O. Sener and S. Savarese. Active learning for convolutional neural networks: A core-set approach. *arXiv preprint arXiv:1708.00489*, 2017.
- [82] P. Sermanet, C. Lynch, Y. Chebotar, J. Hsu, E. Jang, S. Schaal, S. Levine, and G. Brain. Time-contrastive networks: Self-supervised learning from video. In *IEEE International Conference on Robotics and Automation (ICRA)*, pages 1134–1141. IEEE, 2018.
- [83] J. Shang and M. S. Ryoo. Self-supervised disentangled representation learning for third-person imitation learning. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 214–221, 2021.
- [84] J. Shang, S. Das, and M. Ryoo. Learning viewpoint-agnostic visual representations by recovering tokens in 3d space. *Advances in Neural Information Processing Systems*, 35: 31031–31044, 2022.

- [85] J. Shang, K. Kahatapitiya, X. Li, and M. S. Ryoo. Starformer: Transformer with state-action-reward representations for visual reinforcement learning. In *Proceedings of the European Conference on Computer Vision (ECCV)*, 2022.
- [86] J. Shang, X. Li, K. Kahatapitiya, Y.-C. Lee, and M. S. Ryoo. Starformer: Transformer with state-action-reward representations for robot learning. *IEEE transactions on pattern analysis and machine intelligence*, 2022.
- [87] J. Shields, O. Pizarro, and S. B. Williams. Towards adaptive benthic habitat mapping. In *2020 IEEE International Conference on Robotics and Automation (ICRA)*, pages 9263–9270. IEEE, 2020.
- [88] C. Shui, F. Zhou, C. Gagné, and B. Wang. Deep active learning: Unified and principled method for query and training. In *International Conference on Artificial Intelligence and Statistics*, pages 1308–1318. PMLR, 2020.
- [89] D. Silver, T. Hubert, J. Schrittwieser, I. Antonoglou, M. Lai, A. Guez, M. Lanctot, L. Sifre, D. Kumaran, T. Graepel, et al. Mastering chess and shogi by self-play with a general reinforcement learning algorithm. *arXiv preprint arXiv:1712.01815*, 2017.
- [90] S. Sinha, S. Ebrahimi, and T. Darrell. Variational adversarial active learning. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 5972–5981, 2019.
- [91] I. Sorokin, A. Seleznev, M. Pavlov, A. Fedorov, and A. Ignateva. Deep attention recurrent q-network, 2015.
- [92] B. C. Stadie, P. Abbeel, and I. Sutskever. Third-person imitation learning. *arXiv preprint arXiv:1703.01703*, 2017.
- [93] Y. Tang, D. Nguyen, and D. Ha. Neuroevolution of self-interpretable agents. In *Proceedings of the 2020 Genetic and Evolutionary Computation Conference*, pages 414–424, 2020.
- [94] J. Thomason, M. Murray, M. Cakmak, and L. Zettlemoyer. Vision-and-dialog navigation. In *Conference on Robot Learning*, pages 394–406. PMLR, 2020.
- [95] F. Torabi, G. Warnell, and P. Stone. Behavioral cloning from observation. *arXiv preprint arXiv:1805.01954*, 2018.
- [96] A. Tucker, A. Gleave, and S. Russell. Inverse reinforcement learning for video games. *arXiv preprint arXiv:1810.10593*, 2018.
- [97] S. Tunyasuvunakool, A. Muldal, Y. Doron, S. Liu, S. Bohez, J. Merel, T. Erez, T. Lillicrap, N. Heess, and Y. Tassa. dm\_control: Software and tasks for continuous control. *Software Impacts*, 6:100022, 2020. ISSN 2665-9638.
- [98] T. Van de Maele, T. Verbelen, O. Çatal, and B. Dhoedt. Embodied object representation learning and recognition. *Frontiers in Neurorobotics*, 16:840658, 2022.
- [99] H. P. van Hasselt, A. Guez, M. Hessel, V. Mnih, and D. Silver. Learning values across many orders of magnitude. *Advances in neural information processing systems*, 29, 2016.
- [100] M. Vecerik, T. Hester, J. Scholz, F. Wang, O. Pietquin, B. Piot, N. Heess, T. Rothörl, T. Lampe, and M. Riedmiller. Leveraging demonstrations for deep reinforcement learning on robotics problems with sparse rewards. *arXiv preprint arXiv:1707.08817*, 2017.
- [101] F. Wan, T. Yuan, M. Fu, X. Ji, Q. Huang, and Q. Ye. Nearest neighbor classifier embedded network for active learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 10041–10048, 2021.
- [102] S. D. Whitehead and D. H. Ballard. Active perception and reinforcement learning. In *Machine Learning Proceedings 1990*, pages 179–188. Elsevier, 1990.
- [103] D. M. Wolpert, J. Diedrichsen, and J. R. Flanagan. Principles of sensorimotor learning. *Nature reviews neuroscience*, 12(12):739–751, 2011.

- [104] H. Wu, K. Kheterpal, and D. Precup. Self-supervised attention-aware reinforcement learning. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 35, pages 10311–10319, 2021.
- [105] Y. Xie, H. Lu, J. Yan, X. Yang, M. Tomizuka, and W. Zhan. Active finetuning: Exploiting annotation budget in the pretraining-finetuning paradigm. *arXiv preprint arXiv:2303.14382*, 2023.
- [106] J. Yang, Z. Ren, M. Xu, X. Chen, D. J. Crandall, D. Parikh, and D. Batra. Embodied amodal recognition: Learning to move to perceive objects. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 2040–2050, 2019.
- [107] R. Yang, G. Yang, and X. Wang. Neural volumetric memory for visual locomotion control. In *Conference on Computer Vision and Pattern Recognition*, 2023.
- [108] D. Yarats, R. Fergus, A. Lazaric, and L. Pinto. Mastering visual continuous control: Improved data-augmented reinforcement learning. *arXiv preprint arXiv:2107.09645*, 2021.
- [109] T. Yuan, F. Wan, M. Fu, J. Liu, S. Xu, X. Ji, and Q. Ye. Multiple instance active learning for object detection. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 5330–5339, 2021.
- [110] G. Zelinsky, W. Zhang, B. Yu, X. Chen, and D. Samaras. The role of top-down and bottom-up processes in guiding eye movements during visual search. *Advances in neural information processing systems*, 18, 2005.
- [111] T. Zhang, Y. Li, C. Wang, G. Xie, and Z. Lu. Fop: Factorizing optimal joint policy of maximum-entropy multi-agent reinforcement learning. In *International Conference on Machine Learning*, pages 12491–12500. PMLR, 2021.
- [112] A. Zhou, M. J. Kim, L. Wang, P. Florence, and C. Finn. Nerf in the palm of your hand: Corrective augmentation for robotics via novel-view synthesis. *arXiv preprint arXiv:2301.08556*, 2023.
- [113] J.-J. Zhu and J. Bento. Generative adversarial active learning. *arXiv preprint arXiv:1702.07956*, 2017.
- [114] Y. Zhu, J. Wong, A. Mandlekar, R. Martín-Martín, A. Joshi, S. Nasiriany, and Y. Zhu. robo-suite: A modular simulation framework and benchmark for robot learning. In *arXiv preprint arXiv:2009.12293*, 2020.

## A Appendix

### A.1 Learning Curves

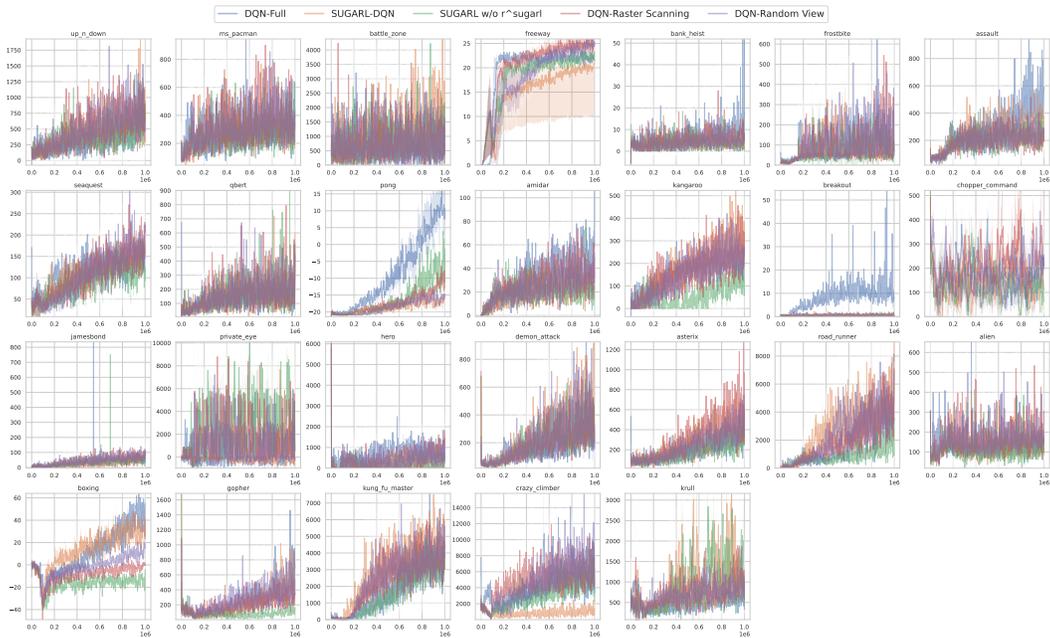


Figure 9: Learning curves of 26 Atari games, under the setting of 50x50 foveal observation size and 20x20 peripheral observation.

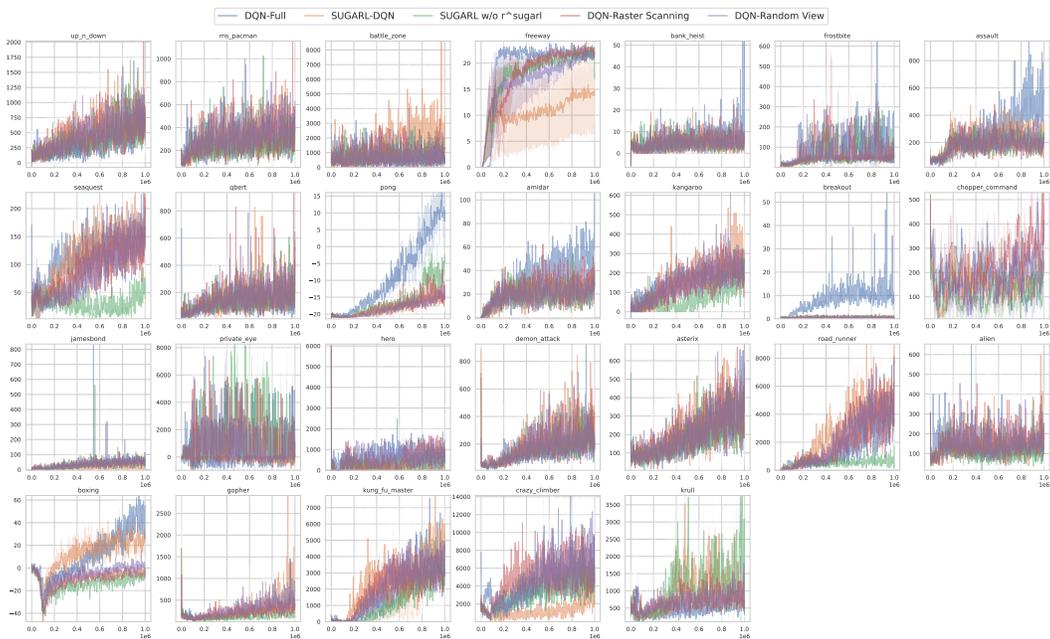


Figure 10: Learning curves of 26 Atari games, under the setting of 30x30 foveal observation size and 20x20 peripheral observation.

### A.2 Hyper-parameter Settings

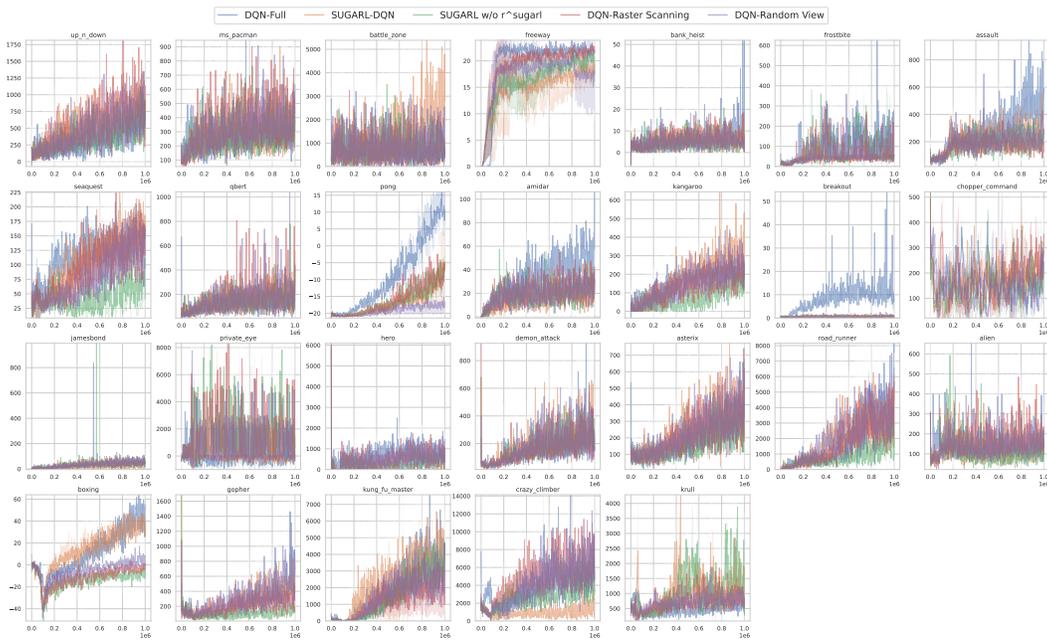


Figure 11: Learning curves of 26 Atari games, under the setting of 20x20 foveal observation size and 20x20 peripheral observation.

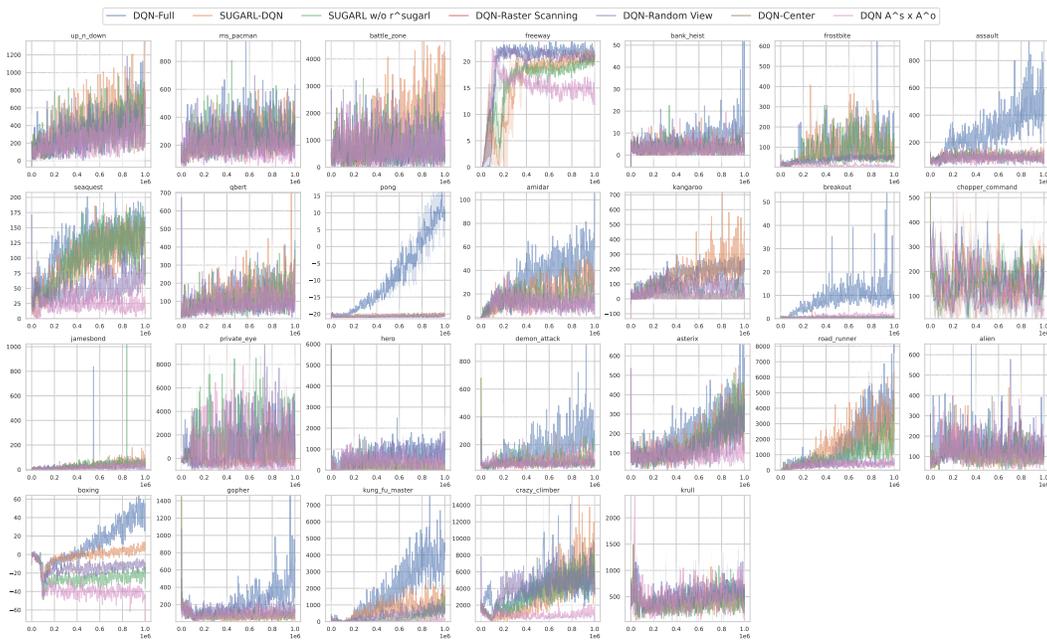


Figure 12: Learning curves of 26 Atari games, under the setting of 50x50 foveal observation size and w/o peripheral observation.

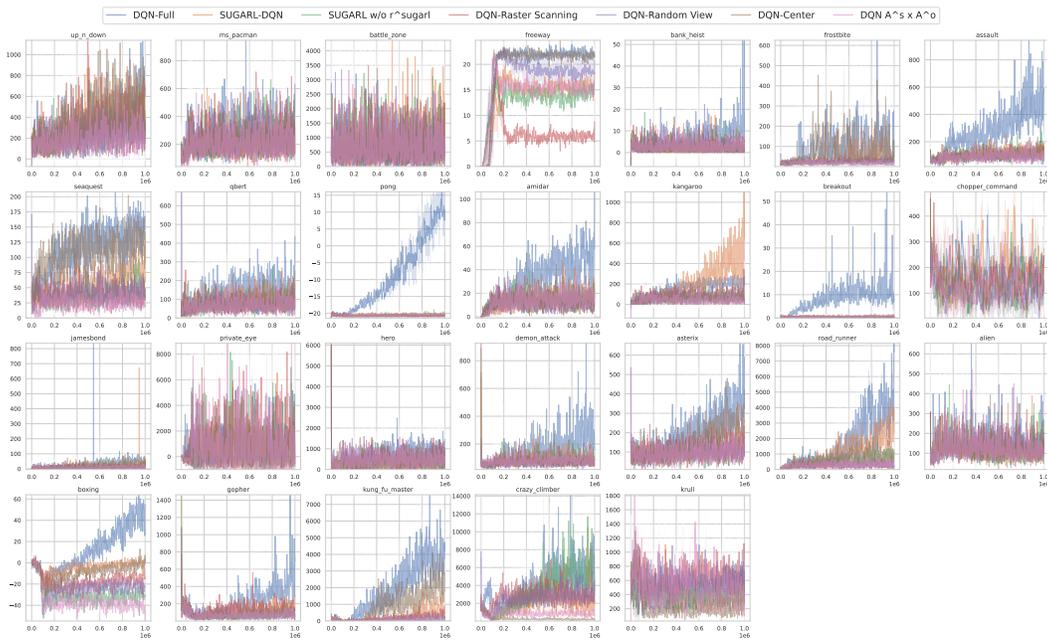


Figure 13: Learning curves of 26 Atari games, under the setting of 30x30 foveal observation size and w/o peripheral observation.

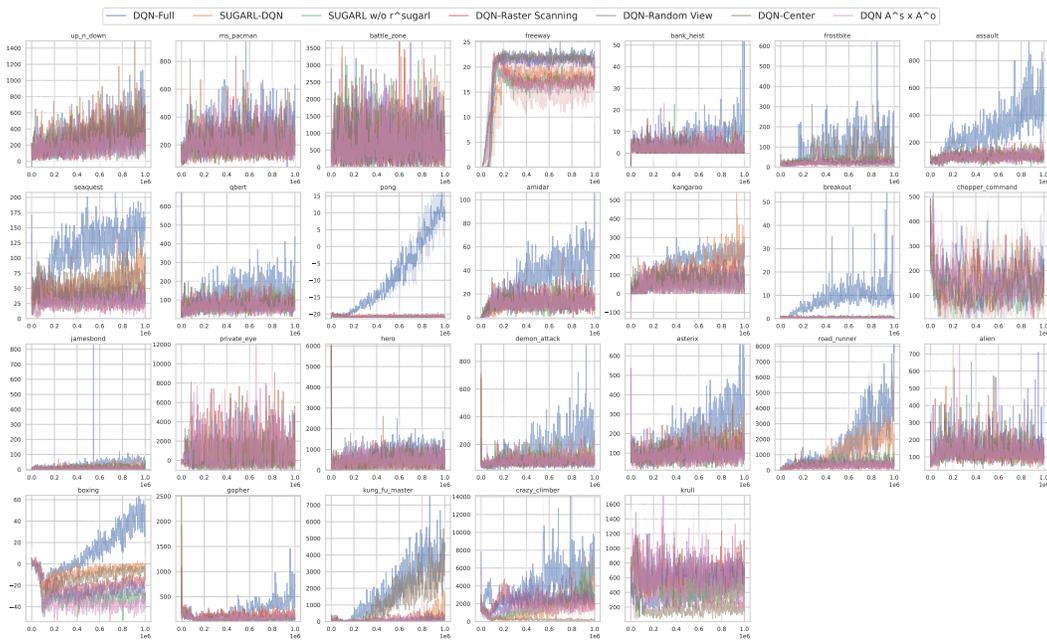


Figure 14: Learning curves of 26 Atari games, under the setting of 20x20 foveal observation size and w/o peripheral observation.

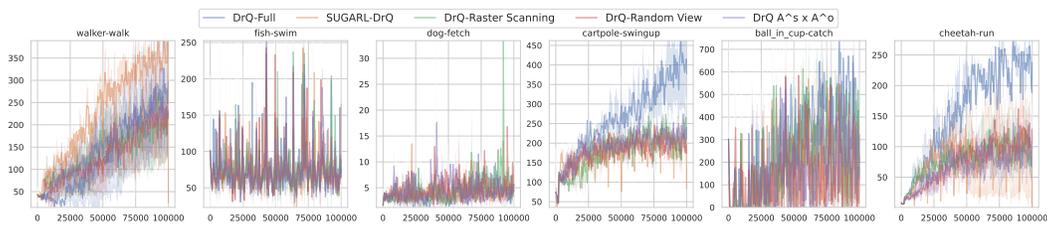


Figure 15: Learning curves of 6 DMC environments, under the setting of 50x50 foveal observation size and w/o peripheral observation.

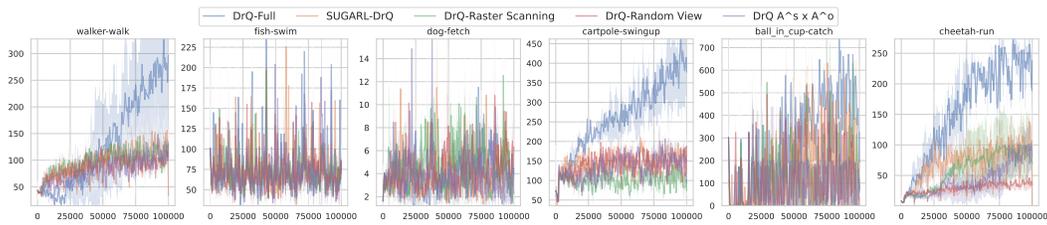


Figure 16: Learning curves of 6 DMC environments, under the setting of 30x30 foveal observation size and w/o peripheral observation.

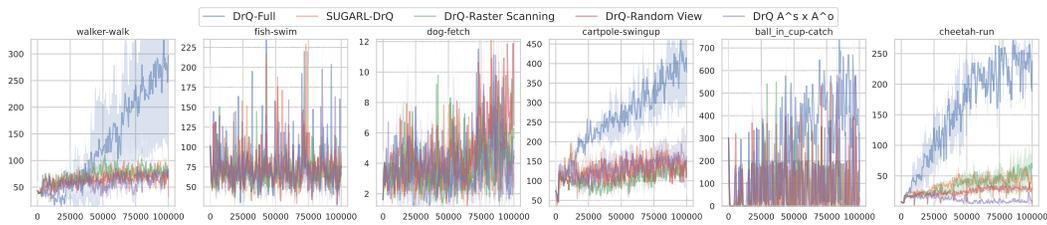


Figure 17: Learning curves of 6 DMC environments, under the setting of 20x20 foveal observation size and w/o peripheral observation.

Table 6: Hyper-parameters for DQN / SUGARL-DQN (on Atari)

Total steps	1,000,000 or 5,000,000
Replay buffer size	100,000
$\epsilon$ start	1.0
$\epsilon$ end	0.01
min $\epsilon$ step	100,000
$\gamma$	0.99
Learning start	80,000
Q network train frequency	4
Target network update frequency	1,000
Learning rate	$10^{-4}$
Batch size	32
Self-understanding module train frequency	4
Self-understanding module learning rate	$10^{-4}$

Table 7: Hyper-parameters for SAC (on Atari)

Total steps	1,000,000
Replay buffer size	100,000
$\gamma$	0.99
Learning start	80,000
Actor train frequency	4
Critic train frequency	4
Target network update frequency	8,000
Actor Learning rate	$3 \times 10^{-4}$
Critic Learning rate	$3 \times 10^{-4}$
Batch size	64
Self-understanding module train frequency	4
Self-understanding module learning rate	$3 \times 10^{-4}$
Visual policy alpha	0.2
Physical policy alpha	autotune
Physical policy target entropy scale	0.2

Table 8: Hyper-parameters for DrQv2 (on DMC)

Total steps	100,000
Replay buffer size	100,000
$\gamma$	0.99
Standard deviation start	1.0
Standard deviation end	0.1
Standard deviation end step	50,000
Standard deviation clip	0.3
Learning start	2,000
Actor train frequency	2
Critic train frequency	2
Target network update frequency	2
Target network exponential moving average weight	0.01
Actor Learning rate	$10^{-4}$
Critic Learning rate	$10^{-4}$
Batch size	256
Self-understanding module train frequency	2
Self-understanding module learning rate	$10^{-4}$
Multiple-step reward	3

Table 9: Hyper-parameters for DrQv2 (on Robosuite)

Total steps	100,000
Replay buffer size	100,000
$\gamma$	0.99
Standard deviation start	1.0
Standard deviation end	0.1
Standard deviation end step	50,000
Standard deviation clip	0.3
Learning start	8,000
Actor train frequency	2
Critic train frequency	2
Target network update frequency	2
Target network exponential moving average weight	0.01
Actor Learning rate	$10^{-4}$
Critic Learning rate	$10^{-4}$
Batch size	256
Self-understanding module train frequency	2
Self-understanding module learning rate	$10^{-4}$
Multiple-step reward	3

Table 10: Environment Settings

<b>Atari</b>	
Gray-scale	True
Full observation size	84x84
Frame stacking	4
Action repeat (frame skipping)	4
Observable area initial location	(0, 0)
Sensory action options	4 × 4 grid
Sensory action space size	16 (abs) or 5 (rel)
PVM number of steps	3
<b>DMC</b>	
Gray-scale	True
Full observation size	84x84
Frame stacking	3
Action repeat (frame skipping)	2
Observable area initial location	(0, 0)
Sensory action options	4 × 4 grid
Sensory action space size	5 (rel)
PVM number of steps	3
<b>Robosuite</b>	
Gray-scale	False
Full observation size	84x84
Frame stacking	3
Action repeat (frame skipping)	2
Observable area initial location	Side View
Sensory action space	continuous relative 5-DoF control
PVM number of steps	3