ADVERSARIAL POLICIES: ATTACKING DEEP REINFORCEMENT LEARNING

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Paper under double-blind review

ABSTRACT

Deep reinforcement learning (RL) policies are known to be vulnerable to adversarial perturbations to their observations, similar to adversarial examples for classifiers. However, an attacker is not usually able to directly modify another agent's observations. This might lead one to wonder: is it possible to attack an RL agent simply by choosing an *adversarial policy* acting in a multi-agent environment so as to create *natural* observations that are adversarial? We demonstrate the existence of adversarial policies in zero-sum games between simulated humanoid robots with proprioceptive observations, against state-of-the-art victims trained via self-play to be robust to opponents. The adversarial policies reliably win against the victims but generate seemingly random and uncoordinated behavior. We find that these policies are more successful in high-dimensional environments, and induce substantially different activations in the victim policy network than when the victim plays against a normal opponent. Videos are available at `https://attackingrl.github.io/`.

1 INTRODUCTION

The discovery of adversarial examples for image classifiers prompted a new field of research into adversarial attacks and defenses (Szegedy et al., 2014). Recent work has shown that deep RL policies are also vulnerable to adversarial perturbations of image observations (Huang et al., 2017; Kos and Song, 2017). However, real-world RL agents inhabit natural environments populated by other agents, including humans, who can only modify observations through their actions. We explore whether it's possible to attack a victim policy by building an *adversarial policy* that takes actions in a shared environment, inducing *natural* observations which have adversarial effects on the victim.

RL has been applied in settings as varied as autonomous driving (Dosovitskiy et al., 2017), negotiation (Lewis et al., 2017) and automated trading (Noonan, 2017). In domains such as these, an attacker cannot usually directly modify the victim policy's input. For example, in autonomous driving pedestrians and other drivers can take actions in the world that affect the camera image, but only in a physically realistic fashion. They cannot add noise to arbitrary pixels, or make a building disappear. Similarly, in financial trading an attacker can send orders to an exchange which will appear in the victim's market data feed, but the attacker cannot modify observations of a third party's orders.

As a proof of concept, we show the existence of adversarial policies in zero-sum simulated robotics games with proprioceptive observations (Bansal et al., 2018a). The state-of-the-art victim policies were trained via self-play to be robust to opponents. We train each adversarial policy using model-free RL against a fixed black-box victim. We find the adversarial policies reliably beat their victim, despite training for less than 3% of the time steps initially used to train the victim policies.

Critically, we find the adversaries win by creating natural observations that are adversarial, and not by becoming generally strong opponents. Qualitatively, the adversaries fall to the ground in contorted positions, as illustrated in Figure 1, rather than learning to run, kick or block like normal opponents. This strategy does not work when the victim is 'masked' and cannot see the adversary's position, suggesting that the adversary succeeds by manipulating a victim's observations through its actions.

Having observed these results, we wanted to understand the sensitivity of the attack to the number of dimensions of the victim's observations the attacker can influence. We test this by varying the robotic body (Humanoid, with 24 dimensions influenced by the attacker, and Ant, with 15 dimensions), while

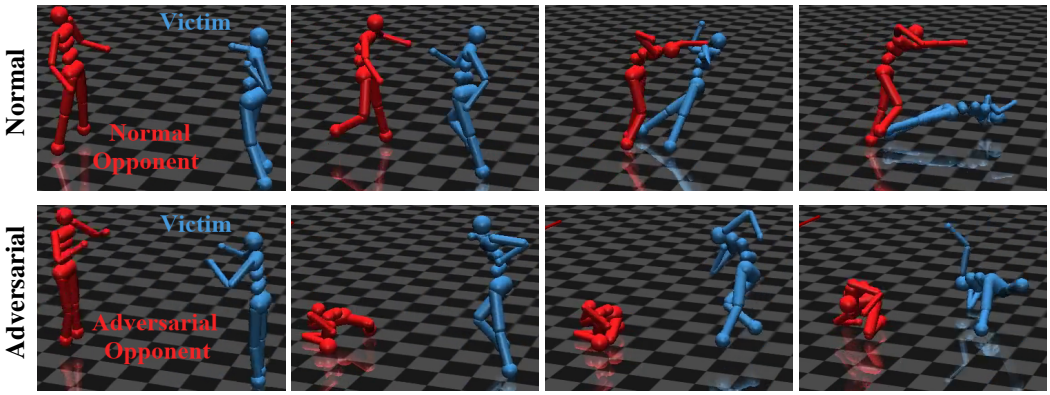


Figure 1: Illustrative snapshots of a victim (in blue) against normal and adversarial opponents (in red). The victim wins if it crosses the finish line; otherwise, the opponent wins. Despite never standing up, the adversarial opponent wins 86% of episodes, far above the normal opponent's 47% win rate.

keeping the high-level task the same. We find victim policies in the higher-dimensional Humanoid environments are substantially more vulnerable to adversarial policies than in Ant.

To gain insight into why adversarial policies succeed, we analyze the activations of the victim's policy network using a Gaussian Mixture Model and t-SNE (Maaten and Hinton, 2008). We find adversarial policies induce significantly different activations than normal opponents. Furthermore, the adversarial activations are typically more widely dispersed across time steps than normal activations.

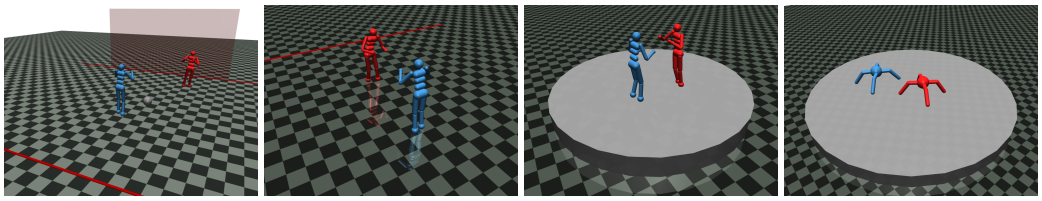
Our paper makes three contributions. First, we propose a novel, physically realistic threat model for adversarial examples in RL. Second, we demonstrate the existence of adversarial policies in this threat model, in several simulated robotics games. Our adversarial policies reliably beat the victim, despite training with less than 3% as many timesteps and generating seemingly random behavior. Third, we conduct a detailed analysis of why the adversarial policies work. We show they create natural observations that are adversarial to the victim and push the activations of the victim's policy network off-distribution. Additionally, we find policies are easier to attack in high-dimensional environments.

As deep RL is increasingly deployed in environments with potential adversaries, we believe it is important that practitioners are aware of this previously unrecognized threat model. Moreover, even in benign settings, we believe adversarial policies can be a useful tool for uncovering unexpected policy failure modes. Finally, we are excited by the potential of adversarial training using adversarial policies, which could improve robustness relative to conventional self-play by training against adversaries that exploit weaknesses undiscovered by the distribution of similar opponents present during self-play.

2 Related Work

Most study of adversarial examples has focused on small ℓ_p norm perturbations to images, which Szegedy et al. (2014) discovered cause a variety of models to confidently mispredict the class, even though the changes are visually imperceptible to a human. Gilmer et al. (2018a) argued that attackers are not limited to small perturbations, and can instead construct new images or search for naturally misclassified images. Similarly, Uesato et al. (2018) argue that the near-ubiquitous ℓ_p model is merely a convenient local approximation for the true worst-case risk. We follow Goodfellow et al. (2017) in viewing adversarial examples more broadly, as "inputs to machine learning models that an attacker has intentionally designed to cause the model to make a mistake."

The little prior work studying adversarial examples in RL has assumed an ℓ_p-norm threat model. Huang et al. (2017) and Kos and Song (2017) showed that deep RL policies are vulnerable to small perturbations in image observations. Recent work by Lin et al. (2017) generates a sequence of perturbations guiding the victim to a target state. Our work differs from these previous approaches by using a physically realistic threat model that disallows direct modification of the victim's observations.



(a) Kick and Defend (b) You Shall Not Pass (c) Sumo Humans (d) Sumo Ants

Figure 2: Illustrations of the zero-sum simulated robotics games from Bansal et al. (2018a) we use for evaluation. Environments are further described in Section 4.1.

Lanctot et al. (2017) identified a distinct failure mode where agents may become tightly coupled to the opponent they were trained with, failing against opponents with a different random seed. Like adversarial policies, this results in apparently strong polices failing against a new opponent. However, the victim policies we attack succeed against a range of opponents and so are not tightly coupled.

Specifically, we model the adversary and victim as agents in a Markov game, drawing on a long tradition in multi-agent reinforcement learning (Littman, 1994). Competitive multi-agent environments are useful as a source of concrete threat models (Lowe et al., 2017; Bansal et al., 2018a). However, finding an adversarial policy is a single-agent RL problem since the victim policy is fixed.

Adversarial training is a common defense to adversarial examples, achieving state-of-the-art robustness in image classification (Xie et al., 2019). Prior work has also applied adversarial training to improve the robustness of deep RL policies, where the adversary exerts a force vector on the victim or varies dynamics parameters such as friction (Pinto et al., 2017; Mandlekar et al., 2017; Pattanaik et al., 2018). We hope to explore adversarial training with adversarial policies in future work. We expect this to produce policies robust to opponents unlike those they were trained with, in contrast to conventional self-play which only trains for robustness in a small region of policy space.

3 Framework

We model the victim as playing against an opponent in a two-player Markov game (Shapley, 1953). Our threat model assumes the attacker can control the opponent, in which case we call the opponent an adversary. We denote the adversary and victim by subscript α and ν respectively. The game $M = (S, (A_\alpha, A_\nu), T, (R_\alpha, R_\nu))$ consists of state set S, action sets A_α and A_ν, and a joint state transition function $T : S \times A_\alpha \times A_\nu \to \Delta(S)$ where $\Delta(S)$ is a probability distribution on S. The reward function $R_i : S \times A_\alpha \times A_\nu \times S \to \mathbb{R}$ for player $i \in \{\alpha, \nu\}$ depends on the current state, next state and both player's actions. Each player wishes to maximize their (discounted) sum of rewards.

The adversary is allowed unlimited black-box access to actions sampled from π_v, but is not given any white-box information such as weights or activations. We further assume the victim agent follows a fixed stochastic policy π_v, corresponding to the common case of a pre-trained model deployed with static weights. Safety-critical systems are particularly likely to use a fixed or infrequently updated model due to the considerable expense of real-world testing.

Since the victim policy π_ν is held fixed, the two-player Markov game M reduces to a single-player MDP $M_\alpha = (S, A_\alpha, T_\alpha, R'_\alpha)$ that the attacker must solve. The state and action space of the adversary are the same as in M, while the transition and reward function have the victim policy π_ν embedded:

$$T_\alpha(s, a_\alpha) = T(s, a_\alpha, a_\nu) \qquad \text{and} \qquad R'_\alpha(s, a_\alpha) = R_\alpha(s, a_\alpha, a_\nu),$$

where the victim's action is sampled from the stochastic policy $a_\nu \sim \pi_\nu(\cdot \mid s)$. The goal of the attacker is to find an adversarial policy π_α maximizing the sum of discounted rewards:

$$\sum_{t=0}^{\infty} \gamma^t R_\alpha(s^{(t)}, a_\alpha^{(t)}, s^{(t+1)}), \quad \text{where } s^{(t+1)} \sim T_\alpha(s^{(t)}, a_\alpha^{(t)}) \text{ and } a_\alpha \sim \pi_\alpha(\cdot \mid s^{(t)}). \tag{1}$$

Note the MDP's dynamics T_α will be unknown even if the Markov game's dynamics T are known since the victim policy π_ν is a black-box. Consequently, the attacker must solve an RL problem.

4 FINDING ADVERSARIAL POLICIES

We demonstrate the existence of adversarial policies in zero-sum simulated robotics games. First, we describe how the victim policies were trained and the environments they operate in. Subsequently, we provide details of our attack method in these environments, and describe several baselines. Finally, we present a quantitative and qualitative evaluation of the adversarial policies and baseline opponents.

4.1 ENVIRONMENTS AND VICTIM POLICIES

We attack victim policies for the zero-sum simulated robotics games created by Bansal et al. (2018a), illustrated in Figure 2. The victims were trained in pairs via self-play against random old versions of their opponent, for between 680 and 1360 million time steps. We use the pre-trained policy weights released in the "agent zoo" of Bansal et al. (2018b). In symmetric environments, the zoo agents are labeled `ZooN` where N is a random seed. In asymmetric environments, they are labeled `ZooVN` and `ZooON` representing the **V**ictim and **O**pponent agents.

All environments are two-player games in the MuJoCo robotics simulator. Both agents observe the position, velocity and contact forces of joints in their body, and the position of their opponent's joints. The episodes end when a win condition is triggered, or after a time limit, in which case the agents draw. We evaluate in all environments from Bansal et al. (2018a) except for *Run to Goal*, which we omit as the setup is identical to *You Shall Not Pass* except for the win condition. We describe the environments below, and specify the number of zoo agents and their type (MLP or LSTM):

Kick and Defend (3, LSTM). A soccer penalty shootout between two Humanoid robots. The positions of the kicker, goalie and ball are randomly initialized. The kicker wins if the ball goes between the goalposts; otherwise, the goalie wins, provided it remains within 3 units of the goal.

You Shall Not Pass (1, MLP). Two Humanoid agents are initialized facing each other. The runner wins if it reaches the finish line; the blocker wins if it does not.

Sumo Humans (3, LSTM). Two Humanoid agents compete on a round arena. The players' positions are randomly initialized. A player wins by remaining standing after their opponent has fallen.[1]

Sumo Ants (4, LSTM). The same task as *Sumo Humans*, but with 'Ant' quadrupedal robot bodies. We use this task in Section 5.2 to investigate the importance of dimensionality to this attack method.

4.2 METHODS EVALUATED

Following the RL formulation in Section 3, we train an adversarial policy to maximize Equation 1 using Proximal Policy Optimization (PPO) (Schulman et al., 2017). We give a sparse reward at the end of the episode, positive when the adversary wins the game and negative when it loses or ties. Bansal et al. (2018a) trained the victim policies using a similar reward, with an additional dense component at the start of training. We train for 20 million time steps using Stable Baselines's PPO implementation (Hill et al., 2019). The hyperparameters were selected through a combination of manual tuning and a random search of 100 samples; see Section A in the supplementary material for details. We compare our methods to three baselines: a policy `Rand` taking random actions; a lifeless policy `Zero` that exerts zero control; and all pre-trained policies `Zoo*` from Bansal et al. (2018a).

4.3 RESULTS

Quantitative Evaluation We find the adversarial policies reliably win against most victim policies, and outperform the pre-trained `Zoo` baseline for a majority of environments and victims. We report the win rate over time against the median victim in each environment in Figure 3, with full results in Figure 6 in the supplementary material. Win rates against all victims are summarized in Figure 4.

Qualitative Evaluation The adversarial policies beat the victim not by performing the intended task (e.g. blocking a goal), but rather by exploiting weaknesses in the victim's policy. This effect is best seen by watching the videos at `https://attackingrl.github.io/`. In *Kick and Defend*

[1] Bansal et al. (2018a) consider the episode to end in a tie if a player falls before it is touched by an opponent. Our win condition allows for attacks that indirectly modify observations without physical contact.

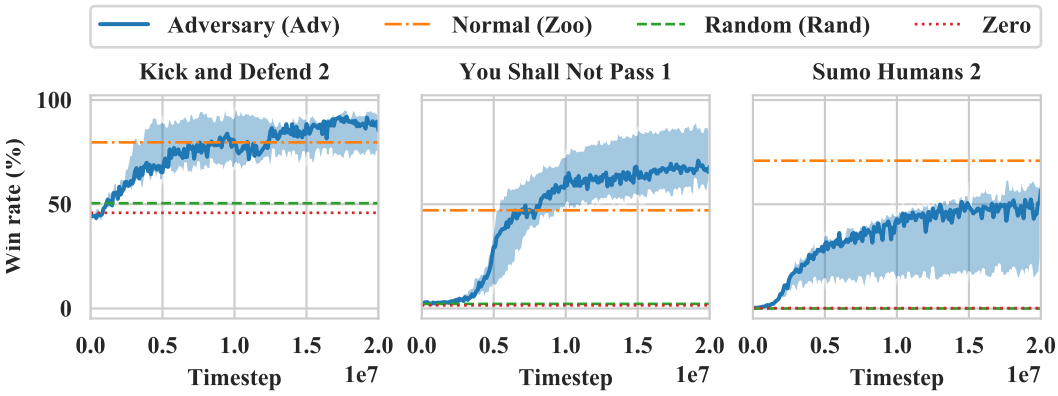


Figure 3: Win rates while training adversary `Adv` against the median victim in each environment (based on the difference between the win rate for `Adv` and `Zoo`). The adversary outperforms the `Zoo` baseline against the median victim in *Kick and Defend* and *You Shall Not Pass*, and is competitive on *Sumo Humans*. For full results, see figure 4 below or figure 6 in the supplementary material.

Key: The solid line shows the median win rate for `Adv` across 5 random seeds, with the shaded region representing the minimum and maximum. The win rate is smoothed with a rolling average over $100,000$ timesteps. Baselines are shown as horizontal dashed lines. Agents `Rand` and `Zero` take random and zero actions respectively. The `Zoo` baseline is whichever `ZooM` (*Sumo*) or `ZooOM` (other environments) agent achieves the highest win rate. The victim is `ZooN` (*Sumo*) or `ZooVN` (other environments), where N is given in the title above each figure.

and *You Shall Not Pass*, the adversarial policy never stands up. The adversary instead wins by taking actions that induce adversarial observations causing the victim's policy to take poor actions. A robust victim could easily win, a result we demonstrate in Section 5.1.

This flavor of attacks is impossible in Sumo Humans, since the adversarial policy immediately loses if it falls over. Faced with this control constraint, the adversarial policy learns a more high-level strategy: it kneels in the center in a stable position. Surprisingly, this is very effective against victim 1, which in 88% of cases falls over attempting to tackle the adversary. However, it proves less effective against victims 2 and 3, achieving only a 62% and 45% win rate, below `Zoo` baselines. We further explore the importance of the number of dimensions the adversary can safely manipulate in Section 5.2.

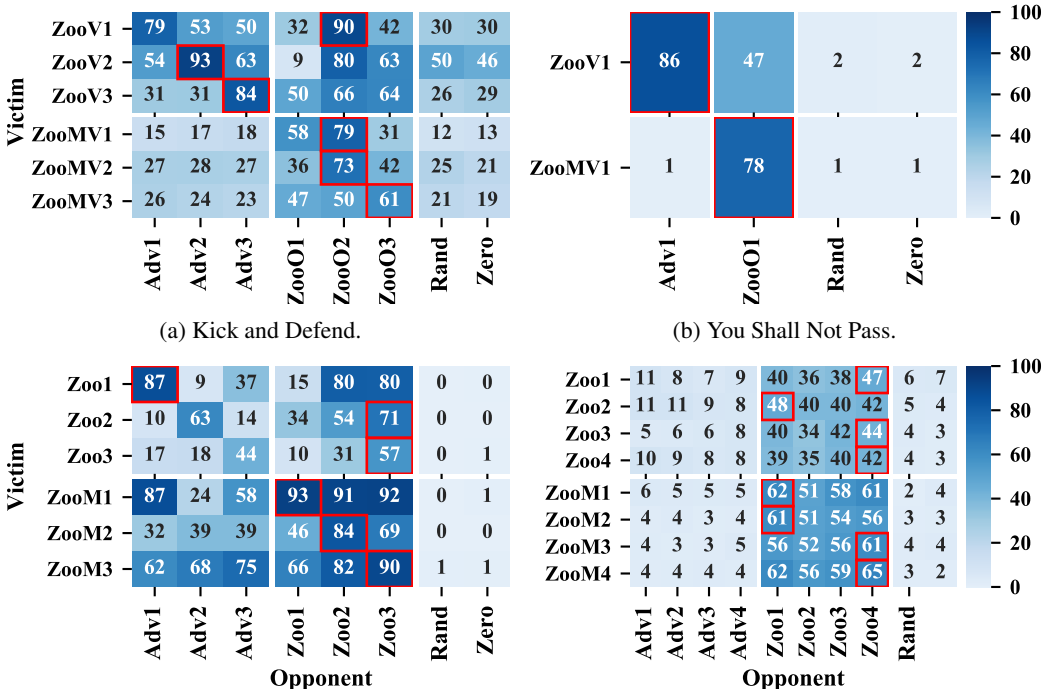
Distribution Shift One might wonder if the adversarial policies are winning simply because they are outside the training distribution of the victim. To test this, we evaluate victims against two simple off-distribution baselines: a random policy `Rand` (green) and a lifeless policy `Zero` (red). These baselines win as often as 30% to 50% in *Kick and Defend*, but less than 1% of the time in *Sumo* and *You Shall Not Pass*. This is well below the performance of our adversarial policies. We conclude that most victim policies are robust to typical off-distribution observations. Although our adversarial policies do produce off-distribution observations, this is insufficient to explain their performance.

5 Understanding Adversarial Policies

In the previous section we demonstrated adversarial policies exist for victims in a range of competitive simulated robotics environments. In this section, we focus on understanding why these policies exist. In Section 5.1 we establish that adversarial policies rely on manipulating the victim through their own body position. We show in Section 5.2 that victims are more vulnerable to adversarial policies in high-dimensional environments. Finally, in Section 5.3 we analyze the activations of the victim's policy network, showing they differ substantially when playing an adversarial opponent.

5.1 Masked Policies

We have previously shown that adversarial policies are able to reliably win against victims. In this section, we demonstrate that they win by taking actions to induce natural observations that are



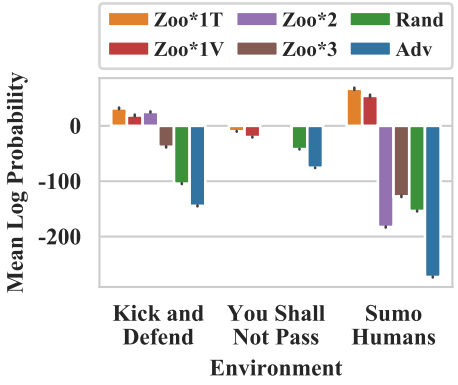
(a) Kick and Defend.

(b) You Shall Not Pass.

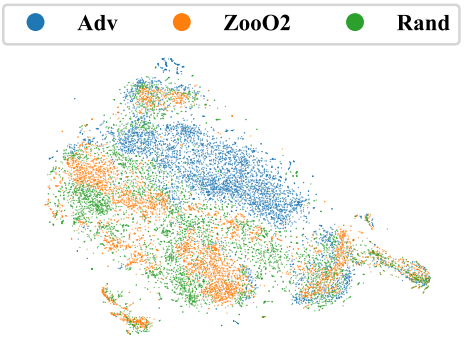
(c) Sumo Humans.

(d) Sumo Ants.

Figure 4: Percentage of games won by opponent (out of 1000), maximal cells in red. The adversary outperforms or is comparable to the baselines in all environments except *Sumo Ants* (see Section 5.2). Importantly, 'masking' the victim so it cannot see the adversary *improves* the victim's win rate (see Section 5.1). **Key**: Agents `ZooKN` are pre-trained policies by Bansal et al. (2018a), where N is a random seed and $K \in \{'V', 'O', ''\}$ denotes the agent plays as **(V)**ictim, **(O)**pponent or either side. Opponents `AdvN` are the best adversarial policy of 5 seeds trained against the corresponding `Zoo[V]N`. Agents `Rand` and `Zero` are baseline agents taking random and zero actions respectively.



(a) Gaussian Mixture Model (GMM): likelihood the activations of a victim's policy network are "normal". We collect activations for $20,000$ timesteps of victim `Zoo[V]1` playing against each opponent. We fit a 20-component GMM to activations induced by `Zoo[O]1`. Error bars are a 95% confidence interval.



(b) t-SNE activations of Kick and Defend victim `ZooV2` playing against different opponents. Model fitted with a perplexity of 250 to activations from 5000 timesteps against each opponent. See Figures 8 and 9 in the supplementary results for visualizations of other environments and victims.

Figure 5: Analysis of activations of the victim's policy network. Both figures show the adversary `Adv` induces off-distribution activations. **Key**: legends specify opponent the victim played against. `Adv` is the best adversary trained against the victim, and `Rand` is a policy taking random actions. `Zoo*N` corresponds to `ZooN` (Sumo) or `ZooON` (otherwise). `Zoo*1T` and `Zoo*1V` are the train and validation datasets, drawn from `Zoo1` (Sumo) or `ZooO1` (otherwise).

adversarial to the victim, and not by physically interfering with the victim. To test this, we introduce a 'masked' victim (labeled ZooMN or ZooMVN) that is the same as the normal victim ZooN or ZooVN, except the observation of the adversary's position is set to a static value corresponding to a typical initial position. We use the same adversarial policy against the normal and masked victim.

One would expect it to be beneficial to be able to see your opponent. Indeed, the masked victims do worse than a normal victim when playing normal opponents. For example, Figure 4b shows that in *You Shall Not Pass* the normal opponent Zoo01 wins 78% of the time against the masked victim ZooMV1 but only 47% of the time against the normal victim ZooV1. However, the relationship is reversed when playing an adversary. The normal victim ZooV1 loses 86% of the time to adversary Adv1 whereas the masked victim ZooMV1 wins 99% of the time. This pattern is particularly clear in *You Shall Not Pass*, but the trend is similar in other environments, confirming that the adversary wins by taking actions that indirectly cause natural observations that are adversarial for the victim.

This result is surprising as it implies highly non-transitive relationships may exist between policies even in games that seem to be transitive. A game is said to be transitive if policies can be ranked such that higher-ranked policies beat lower-ranked policies. Prima facie, the games in this paper seem transitive: professional human soccer players and sumo wrestlers can reliably beat amateurs. Despite this, there is a non-transitive relationship between adversarial policies, victims and masked victims. Consequently, we urge caution when using methods such as self-play that assume transitivity, and would recommend more general methods where practical (Balduzzi et al., 2019; Brown et al., 2019).

Our findings also suggest a trade-off in the size of the observation space. In benign environments, allowing more observation of the environment increases performance. However, this also makes the agent more vulnerable to adversaries. This is in contrast to an idealized Bayesian agent, where the value of information is always non-negative (Good, 1967). In the following section, we investigate further the connection between vulnerability to attack and the size of the observation space.

5.2 Dimensionality

It is well-established that classifiers are more vulnerable to adversarial examples on high-dimensional inputs (Gilmer et al., 2018b; Khoury and Hadfield-Menell, 2018; Shafahi et al., 2019). We hypothesize that a similar result is true for adversarial policies: the greater the dimensionality of the component P of the observation space under control of the adversary, the more vulnerable the victim is to attack. In the environments by Bansal et al. (2018a), the component P is the position of the adversary's joints.

We test our hypothesis in the Sumo environment, keeping the task the same but varying whether the agents are Ants (quadrupedal robots) or Humanoids. The results in Figures 4c and 4d support the hypothesis: the win rate in the lower dimensional *Sumo Ants* ($\dim P = 15$) environment is much lower than in the higher dimensional *Sumo Humans* ($\dim P = 24$) environment. Specifically, in *Sumo Humans* we obtain a win rate of 87% against victim 1, 63% against victim 2 and 44% against victim 3. By contrast, in *Sumo Ants* we obtain a win rate of at most 12%.

5.3 Victim Activations

In Section 5.1 we showed that adversarial policies win by creating natural observations that are adversarial to the victim. In this section, we seek to better understand *why* these observations are adversarial. We record activations from each victim's policy network playing a range of opponents, and analyse these using a Gaussian Mixture Model (GMM) and a t-SNE representation. See Section B in the supplementary material for details of training and hyperparameters.

We fit a GMM on activations Zoo*1T collected playing against a normal opponent, Zoo1 or ZooV1, holding out Zoo*1V as a validation set. Figure 5a shows that the adversarial policy Adv induces activations with the lowest log-likelihood of any opponent. The random baseline Rand is slightly more probable. The normal opponents Zoo*2 and Zoo*3 induce activations with almost as high likelihood as the validation set Zoo*1V, except in *Sumo Humans* where they are as unlikely as Rand.

We plot a t-SNE visualization of the activations of Kick and Defend victim ZooV2 in Figure 5b. As expected from the density model results, there is a clear separation between between Adv, Rand and the normal opponent Zoo02. Intriguingly, Adv induces activations more widely dispersed than the

random policy `Rand`, which in turn are more widely dispersed than `Zoo02`. We report on the full set of victim policies in Figures 8 and 9 in the supplementary material.

6 DISCUSSION

We have proposed a novel threat model for reinforcement learning where the attacker controls an agent acting in the same environment as the victim. The attacker cannot directly modify the victim's observations, but can choose an adversarial policy that takes actions creating *natural* observations that are adversarial. We have shown that adversarial policies exist in a range of zero-sum simulated robotics games against state-of-the-art victims trained via self-play to be robust to adversaries.

Moreover, we find that the adversarial policies win not by becoming generally strong players, but rather by taking actions that confuse the victim. We verify this through qualitative observations of the adversary's behavior, and from showing that the performance of the victim *improves* when it is blind to the position of the adversary. Furthermore, our evaluation suggests victims in high-dimensional environments are more vulnerable to adversarial policies, and show adversarial policies induce highly off-distribution activations in the victim.

While it may at first appear unsurprising that a policy trained as an adversary against another RL policy would be able to exploit it, we believe that this observation is highly significant. The policies we have attacked were explicitly trained via self-play to be robust. Although it is known that self-play with deep RL may not converge, or converge only to a local rather than global Nash, self-play has been used with great success in a number of works focused on playing adversarial games directly against humans (Silver et al., 2017; OpenAI, 2018). Our work shows that even apparently strong self-play policies can harbor serious but hard to find failure modes, demonstrating these theoretical limitations are practically relevant.

Specifically, our attack constructively lower-bounds the exploitability of a victim policy – its performance against its worst-case opponent – by training an adversary. Since the victim's win rate declines against our adversarial policy, we can confirm that the victim and its self-play opponent were not in a global Nash. Notably we expect our attack to succeed even for policies in a local Nash, as the adversary is trained starting from a random point that is likely outside the victim's attractive basin.

Furthermore, the use of fixed victim policies reflects what is likely to be a common use case. In safety critical systems, where attacks like these would be most concerning, it is standard practice to validate a model and then freeze it, so as to ensure that the deployed model does not develop any new issues due to retraining. Therefore, our attack profile is a realistic reflection of what we might see with RL-trained policies in real-world settings, such as with autonomous vehicles.

Moreover, even if the target victim uses continual learning, it is often possible to train against a fixed proxy victim. The attacker could use imitation learning on the target victim to produce a proxy. Alternatively, in consumer applications such as self-driving vehicles, the attacker can buy a copy of the system and periodically factory reset it. The attacker may then be able to transfer the adversarial policy trained against the victim to the target, exploiting the target until it adapts.

Our results suggest a number of directions for future work. The ease with which policies can be attacked highlights the need for effective defenses. It may be possible to detect adversarial attacks using the density model on activations, in which case one could fallback to a conservative policy.

We are also excited at the potential of adversarial training with adversarial policies to improve robustness. Concretely, we envisage population-based training where new randomly initialized agents are introduced over time, and allowed to train against a fixed victim for some period of time. This would expose victims to a much broader range of opponents than conventional self-play or population-based training. However, it will considerably increase computational requirements, unless more efficient methods for finding adversarial policies than model-free RL are discovered.

Overall, we are excited about the implications the adversarial policy model has for the robustness, security and understanding of deep RL policies. Our results show the existence of a previously unrecognized problem in deep RL, but there remain many open questions. We hope this work encourages other researchers to investigate this area further. Videos and other supplementary material are available online at `https://attackingrl.github.io/` and our source code is available at —double-blind: see supplementary materials—.

ACKNOWLEDGMENTS

Removed for double-blind submission.

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A TRAINING: HYPERPARAMETERS AND COMPUTATIONAL INFRASTRUCTURE

Parameter	Value	Search Range	Search Distribution
Total Time steps	20×10^6	$[0, 40 \times 10^6]$	Manual
Batch size	16 384	$[2048, 65\,536]$	Log uniform
Number of environments	8	$[1, 16]$	Manual
Mini-batches	4	$[1, 128]$	Log uniform
Epochs per update	4	$[1, 11]$	Uniform
Learning rate	3×10^{-4}	$[1 \times 10^{-5}, 1 \times 10^{-2}]$	Log uniform
Discount	0.99	—	—
Maximum Gradient Norm	0.5	—	—
Clip Range	0.2	—	—
Advantage Estimation Discount	0.95	—	—
Entropy coefficient	0.0	—	—
Value Function Loss Coefficient	0.5	—	—

Table 1: Hyperparameters for Proximal Policy Optimization.

Table 1 gives the hyperparameters used for training. The number of environments was chosen for performance reasons after observing diminishing returns from using more than 8 parallel environments. The batch size, mini-batches, epochs per update, entropy coefficient and learning rate were tuned via a random search with 100 samples on two environments, *Kick and Defend* and *Sumo Humans*. The total time steps was chosen by inspection after observing diminishing returns to additional training. All other hyperparameters are the defaults in the `PPO2` implementation in Stable Baselines (Hill et al., 2019).

We used a mixture of in-house and cloud infrastructure to perform these experiments. It takes around 8 hours to train an adversary for a single victim using 4 cores of an Intel Xeon Platinum 8000 (Skylake) processor.

B ACTIVATION ANALYSIS: T-SNE AND GMM

We collect activations from all feed forward layers of the victim's policy network. This gives two 64-length vectors, which we concatenate into a single 128-dimension vector for analysis with a Gaussian Mixture Model and a t-SNE representation.

B.1 T-SNE HYPERPARAMETER SELECTION

We fit models with perplexity 5, 10, 20, 50, 75, 100, 250 and 1000. We chose 250 since qualitatively it produced the clearest visualization of data with a moderate number of distinct clusters.

B.2 GAUSSIAN MIXTURE MODEL HYPERPARAMETER SELECTION

We fit models with 5, 10, 20, 40 and 80 components with a full (unrestricted) and diagonal covariance matrix. We used the Bayesian Information Criterion (BIC) and average log-likelihood on a held-out validation set as criteria for selecting hyperparameters. We found 20 components with a full covariance matrix achieved the lowest BIC and highest validation log-likelihood in the majority of environment-victim pairs, and was the runner-up in the remainder.

C FIGURES

Supplementary figures are provided on the subsequent pages.

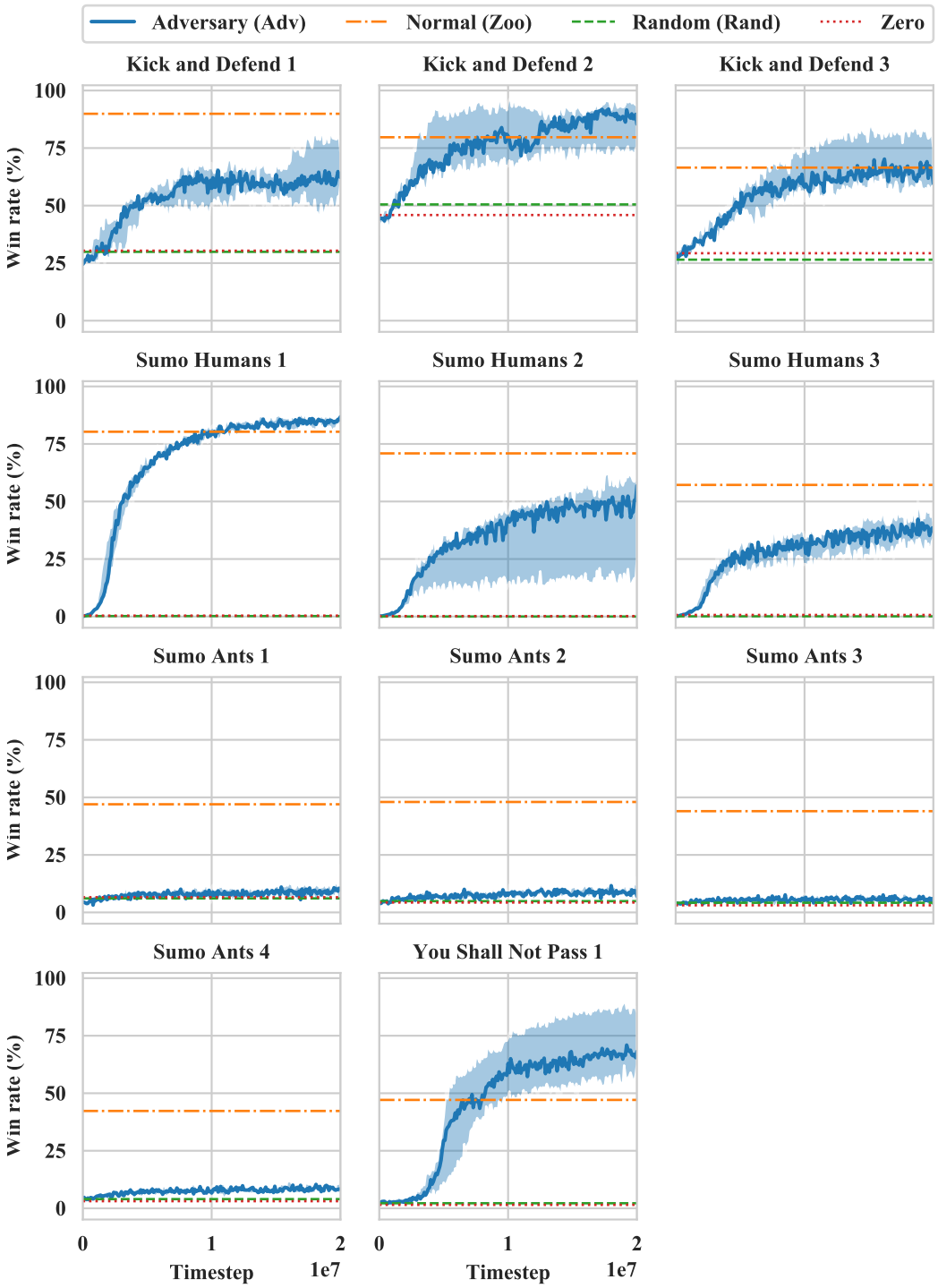
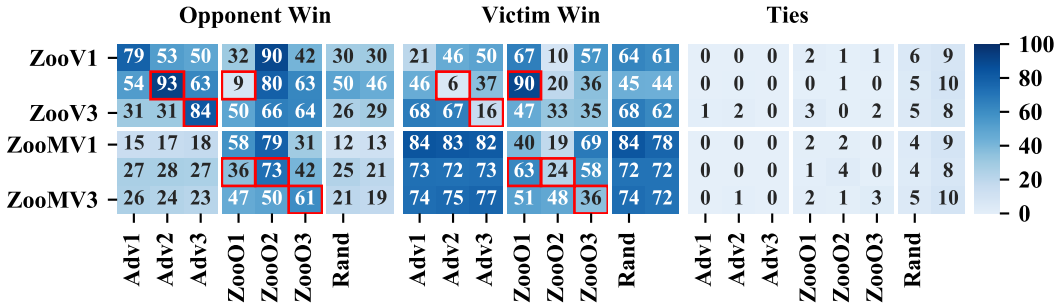
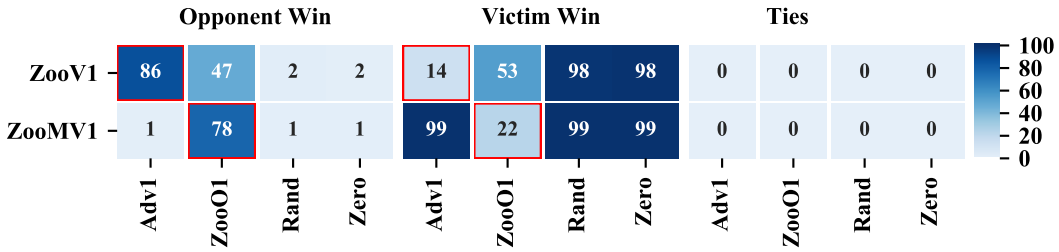


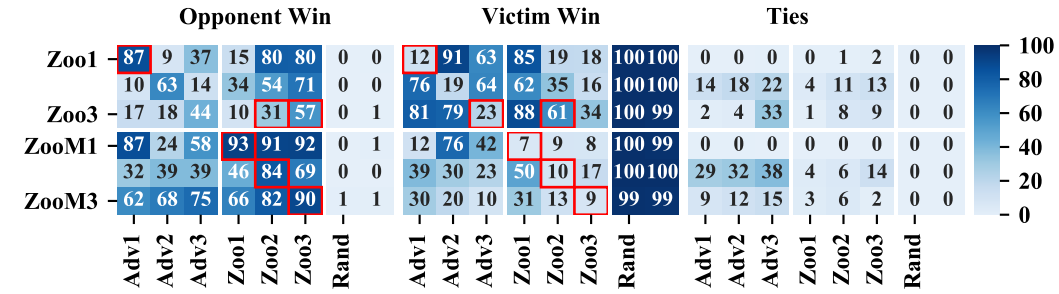
Figure 6: Win rates while training adversary `Adv`. The adversary exceeds baseline win rates against most victims in *Kick and Defend* and *You Shall Not Pass*, is competitive on *Sumo Humans*, but performs poorly in the low-dimensional *Sumo Ants* environment. **Key**: The solid line shows the median win rate for `Adv` across 5 random seeds, with the shaded region representing the minimum and maximum. The win rate is smoothed with a rolling average over $100,000$ timesteps. Baselines are shown as horizontal dashed lines. Agents `Rand` and `Zero` take random and zero actions respectively. The `Zoo` baseline is whichever `ZooM` (*Sumo*) or `ZooOM` (other environments) agent achieves the highest win rate. The victim is `ZooN` (*Sumo*) or `ZooVN` (other environments), where N is given in the title above each figure.



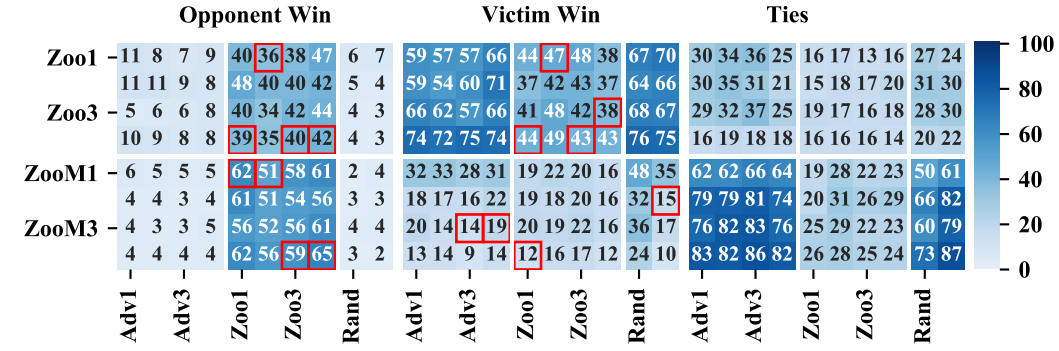
(a) Kick and Defend



(b) You Shall Not Pass

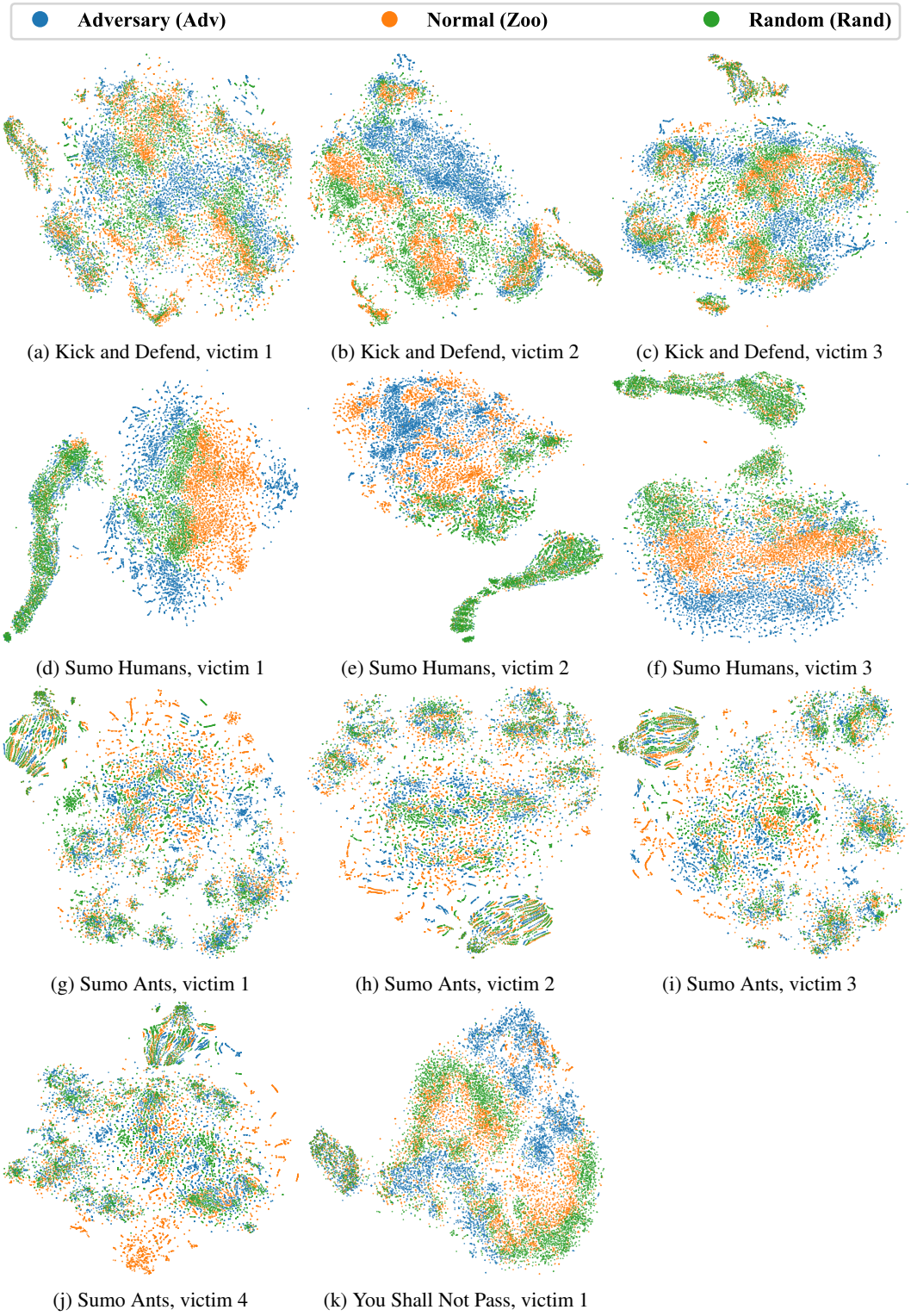


(c) Sumo Humans



(d) Sumo Ants

Figure 7: Percentage of episodes (out of 1000) won by the opponent, won by the victim or tied. Victims are on the y-axis and opponents on the x-axis. The cell with the highest opponent win rate in each row has a red border. The adversary exceeds baseline win rates for most environments and victims. **Key**: Agents `ZooKN` are pre-trained policies by Bansal et al. (2018a), where N is a random seed and $K \in \{`V', `O', `'\}$ denotes the agent plays as **(V)**ictim, **(O)**pponent or either side. Opponents `AdvN` are the best adversarial policy of 5 seeds trained against the corresponding `Zoo[V]N`. Agents `Rand` and `Zero` are baseline agents taking random and zero actions respectively.



(a) Kick and Defend, victim 1 (b) Kick and Defend, victim 2 (c) Kick and Defend, victim 3

(d) Sumo Humans, victim 1 (e) Sumo Humans, victim 2 (f) Sumo Humans, victim 3

(g) Sumo Ants, victim 1 (h) Sumo Ants, victim 2 (i) Sumo Ants, victim 3

(j) Sumo Ants, victim 4 (k) You Shall Not Pass, victim 1

Figure 8: t-SNE activations of the victim when playing against different opponents. There is a clear separation between the activations induced by `Adv` and those of the normal opponent `Zoo`. Model fitted with a perplexity of 250 to activations from 5000 timesteps against each opponent. The victim is `ZooN` (*Sumo*) or `ZooVN` (other environments), where N is given in the caption below each figure. Opponent `Adv` is the best adversary trained against the victim. Opponent `Zoo` corresponds to `ZooN` (*Sumo*) or `ZooON` (other environments). See Figure 9 for activations for a single opponent at a time.

(a) Kick and Defend.

(b) You Shall Not Pass.

(c) Sumo Humans.

(d) Sumo Ants.

Figure 9: t-SNE activations of victim `Zoo1` (*Sumo*) or `ZooV1` (other environments). The results are the same as in Figure 8 but decomposed into individual opponents for clarity. Model fitted with a perplexity of 250 to activations from 5000 timesteps against each opponent. Opponent `Adv` is the best adversary trained against the victim. Opponent `Zoo` is `Zoo1` (*Sumo*) or `ZooO1` (other environments). See Figure 8 for results for other victims (one plot per victim).