Objective Robustness in Deep Reinforcement Learning

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Abstract

We study objective robustness failures, a type of out-of-distribution robustness failure in reinforcement learning (RL). Objective robustness failures occur when an RL agent retains its capabilities out-of-distribution yet pursues the wrong objective. This kind of failure presents different risks than the robustness problems usually considered in the literature, since it involves agents that leverage their capabilities to pursue the wrong objective rather than simply failing to do anything useful. We provide the first explicit empirical demonstrations of objective robustness failures and present a partial characterization of its causes.

1 Introduction

Out of distribution (OOD) robustness, performing well on test data that is not distributed identically to the training set, is a fundamental problem in machine learning [4]. This is crucial since in many applications it is not feasible to collect data distributed identically to that which the model will encounter in deployment.

In this work, we focus on a particularly concerning type of OOD robustness called objective robustness [16], which we study in the RL setting. Usually, when an RL model is deployed out-of-distribution, the model either performs well or simply fails to take useful actions. However, there exists an alternative failure mode in which the agent pursues an objective other than the training reward while retaining all or most of the capabilities it had on the training distribution. We call this kind of failure an objective robustness failure and distinguish it from capability robustness failures. To highlight and illustrate this class of failures, we provide empirical demonstrations of the phenomenon in deep RL agents—to our knowledge, this is the first time it has been demonstrated empirically.

While capability robustness failures are concerning, objective robustness failures are potentially more dangerous, since an agent that capably pursues an incorrect objective can leverage its capabilities to visit arbitrarily bad states. In contrast, the only risks from capability robustness failure are those of accidents due to its incompetence. Our main contributions are:

- We highlight the class of objective robustness failures, differentiate it from other robustness problems, and discuss why it is important to address (Section 2).
- We demonstrate that objective robustness failures occur in practice by training deep RL agents on the Procgen benchmark [27], a set of diverse procedurally generated environments designed to induce robust generalization, and deploying them on slightly modified environments (Section 3).

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We show that objective robustness failures may be alleviated by increasing the diversity of the training distribution so that the agent may learn to distinguish the reward from potential proxies for it (Section 3.1.1).

2 Objective Robustness

Our focus is on a sub-problem of the more general problem of out-of-distribution (OOD) robustness, which is usually studied in the supervised learning setting, where it is defined as achieving good test error even when the test data is sampled from a different distribution than the training data. It is widely known that deep learning systems may fail in unexpected ways when deployed out-of-distribution; for example, a classifier trained on images of cows in Alpine pastures will typically fail to recognize an image of a cow that is taken on a sandy beach [7; 4].

We focus on the reinforcement learning setting [34], in which a system is trained to take actions in an environment in order to maximize a given reward. In this setting, the problem is to achieve high return out-of-distribution. OOD robustness problems frequently arise in RL—here are a few examples:

1. A robot is trained in a simulation where data is plentiful. It is then deployed in the real world, where it encounters subtle differences in physical parameters [3].
2. A factory wants to use deep RL for a process control application. The agent is trained on episodes of fixed length. When it is deployed in the real world, the episode never ends (there are no episode resets in the real world), and the distribution of observations slowly drifts over time as its context in the world changes.

2.1 Defining objective robustness

A deep RL agent is trained to maximize reward \( R: S \times A \times S \rightarrow \mathbb{R} \), where \( S \) and \( A \) are the sets of all valid states and actions, respectively. Assume that the agent is deployed under distributional shift; that is, an aspect of the environment (and therefore the distribution of observations) changes at test time. If the agent now achieves low reward in the new environment because it continues to act capably yet appears to optimize a different objective \( R' \neq R \), then we say the agent underwent an objective robustness failure. We call \( R' \) the behavioral objective of the agent.

We must specify what counts as a behavioral objective (for example, we wish to avoid ascribing a behavioral objective to an agent that simply acts randomly). To do this, we understand the behavioral objective as equivalent to the notion of a “goal” under the intentional stance [10]: a system has one if describing the system as pursuing it is useful for predicting that system’s behavior. In particular, we do not assume that the behavioral objective is represented explicitly by the agent, although this may
sometimes be the case. This rules out e.g. an objective that is simply the indicator function for the policy.

Our primary motivation for identifying this class of failures is that objective robustness failures—failures in which systems take competent yet misaligned actions when deployed out-of-distribution—have the potential to be particularly dangerous. Other types of failures are bounded in the damage they can do: the worst that can happen is an accident resulting from incompetence (say, a self-driving car failing to brake). In contrast, an agent that pursues an incorrect objective can perform arbitrarily badly relative to the true reward and indeed becomes more dangerous the more capable it is.

2.2 Properties and causes of objective robustness failures

When should we expect models to be objective robust? We begin by identifying prerequisites for objective robustness failure:

1. The training environment must be diverse enough to learn sufficiently robust capabilities. If this is not the case, then RL algorithms tend to memorize simple action sequences that work in the training environment but are not robust under distributional shift.

2. There must exist some proxy $R' : S \times A \times S \rightarrow \mathbb{R}$ that approximately tracks the true reward on the training distribution.

3. The proxy and the true reward come apart on the OOD test environment.

While these are plausible necessary conditions for objective robustness failure, they are by no means sufficient since, by themselves, they do not guarantee that the model learns to follow the proxy reward $R'$ instead of the true reward. However, assumptions (1) and (2) are also very weak: almost every real-world problem requires a diverse training environment (to achieve capability robustness), and proxies are common in complex environments. Thus objective robustness failure depends mostly on whether the inductive biases of the model prime it to learn a proxy that then (3) diverges from the true objective on the test set.

What proxies then do models tend to learn? Following Hubinger et al. [18], we (non-exhaustively) list factors that increase the likelihood of learning a particular proxy $R'$.

- The proxy $R'$ is simpler than the true reward $R$.
- The true reward $R$ is sparse, but the proxy $R'$ is dense [31].
- The true reward $R$ is computationally hard to predict without using the proxy, while the proxy is easily predictable.
- If $R$ is hard to predict, then large model capacity may make objective robustness failure less likely, because the model is better able to model the true reward.

As an example for such proxies, consider human evolution. While very different from SGD, biological evolution is (to an approximation) a local optimization process that maximizes inclusive genetic fitness. Humans, however, generally have no desire to maximize the number of our descendants. Instead, we pursue objectives which in the ancestral environment were good proxies for fitness, such as friendship, food, and love. This illustrates a general phenomenon: given a challenging objective, complex environments are rife with proxies for and sub-goals of that objective, many of which are more dense or easier to predict than the true objective. In addition, human evolution illustrates how such proxies can come apart from the true objective under distributional shift: in the ancestral environment humans were driven to eat high-caloric foods, which in the modern world often leads to obesity. We illustrate this sort of shift in a simple experiment in Section 3.3 that relies on sub-goals. This suggests that objective robustness will be a relevant problem in complex, real-world tasks.

Our experiments have been designed to show as clearly as possible that the robustness failures demonstrated are different from those usually considered in the literature. For example, a natural interpretation of our results in CoinRun in Section 3.1 is that the agent has learned a robust capability to avoid obstacles and navigate the levels, but a non-robust objective, since its behavior out-of-distribution is better described by “get to the end of the level” than “go to the coin”. [2]

After all, Procgen [27] was designed to test (capability) generalization in deep RL.
By empirically demonstrating this kind of failure for the first time, we hope to illustrate how it is different from the kind of robustness failure that is usually considered in the literature and help others think more clearly about objective robustness. Though it may seem unreasonable to expect the agent to identify the coin, not the end of the level, as the marker of the true reward when the two were indistinguishable during training, it is precisely this unidentifiability of the true reward that makes objective robustness a difficult problem. More complex and realistic environments are also likely to have proxies which are reliably correlated with the reward during training but may cease to be correlated with it out-of-distribution. In this way, objective robustness is similar to the problem of unidentifiability in IRL [1], as discussed in Section 4.

3 Experiments

Here, we provide simple empirical demonstrations of objective robustness failures. Each experiment is an example of an agent that learns to perform capably when deployed out-of-distribution, but pursues a behavioral objective that is different from the objective for which it was optimized. Video examples of objective robustness failures in all of the following environments can be found in the supplementary materials.

All environments are adapted from the Procgen benchmark [27]. This benchmark is built to study sample efficiency and generalization to within-distribution tasks. Agents are tasked with performing well in an arcade-like video game from pixel observations. The environments are procedurally generated and thus diverse; to perform well, an agent is forced to learn strategies that work in a wide range of task settings and difficulty and cannot rely on e.g. memorizing a small number of trajectories to solve a fixed set of levels.

Implementational Details  For all environments, we use an Actor-Critic architecture using Proximal Policy Optimization (PPO) [33]. Hyperparameters can be found in the Appendix. All models are implemented in PyTorch [29], and our implementation is based on a codebase by Lee [24]. Unless otherwise stated, models are trained on 100k procedurally generated levels for 200M timesteps. Each training run required approximately 30 GPU hours of compute on a V100.

Different kinds of failure  The experiments illustrate different flavors of objective robustness failures. **Action space proxies** (CoinRun and Maze I): the agent substitutes a simple action space proxy (“move right”) for the true reward, which could have been identified in terms of a simple feature in its input space (the yellow coin/cheese). **Observation ambiguity** (Maze II): The observations contain multiple features that identify the goal state, which come apart in the OOD test distribution. **Instrumental goals** (Keys and Chests): The agent learns an objective (collecting keys) that is only instrumentally useful to acquiring the true reward (opening chests).

3.1 CoinRun

In CoinRun, a platformer, the agent spawns on the left side of the level and has to avoid enemies and obstacles to get to a coin (the reward) at the far right of the level. To induce an objective robustness failure, we create a test environment in which coin position is randomized (but accessible). The agent is trained on vanilla CoinRun and deployed in the modified test environment.

At test time, the agent generally ignores the coin completely. While the agent sometimes runs into the coin by accident, it often misses it and proceeds to the end of the level, as shown in Figure 1. It is clear from this demonstration that the agent has not learned to go after the coin; instead, it has learned the proxy "reach the far right end of the level." It competently achieves this objective, but test reward is low.

3.1.1 Varying how often the coin is randomly placed in training

To test how stable the objective robustness failure is, we train a series of agents on environments which vary in how often the coin is placed randomly. We then deploy those agents in the test environment in which coin position is always randomized. Results can be seen in Figure 2, which shows the frequencies of two different outcomes, 1) failure of capability: the agent dies or gets stuck, thus neither getting the coin nor to the end of the level, and 2) failure of objective: the agent misses the
coin and navigates to the end of the level. As expected, as the diversity of the training environment increases, the proportion of objective robustness failures decreases, as the model learns to pursue the coin instead of going to the end of the level.

![Figure 2: How diverse does the training distribution need to be to induce objective robustness? We train agents in a CoinRun environment in which the coin is placed randomly {0, 2, 3, 6, 11} % of the time, and keep track of how often the agent navigates to the end of the level while ignoring the coin.](image)

3.2 Maze

3.2.1 Variant 1

We modify the Procgen Maze environment in order to implement an idea from Hubinger [17]. In this environment, a maze is generated using Kruskal’s algorithm [23], and the agent is trained to navigate towards a piece of cheese located at a random spot in the maze. Instead of training on the original environment, we train on a modified version in which the cheese is always located in the upper right corner of the maze (Figure 3).

When deployed in the original Maze environment at test time, the agent does not perform well; it ignores the randomly placed objective, instead navigating to the upper right corner of the maze as usual. Using the terminology of Section 2: the training objective is to reach the cheese, but the behavioral objective of the learned policy is to navigate to the lower right corner.

3.2.2 Variant 2

We hypothesize that in CoinRun, the policy that always navigates to the end of the level is preferred because it is simple in terms of its action space: simply move as far right as possible. The same is true for the Maze experiment in Section 3.2.1 where the agent has learned to navigate to the top right corner. In both experiments, the objective robustness failure arises because a visual feature (coin / cheese) and a positional feature (right / top right) come apart at test time, and the inductive biases of the model favor the latter. However, objective robustness failures can also arise due to other kinds of distributional shift. To illustrate this, we present a simple setting in which there is no positional feature that favors one objective over the other; instead, the agent is forced to choose between two ambiguous visual cues.

We train an RL agent on a version of the Procgen Maze environment where the reward is a randomly placed yellow gem. At test time, we deploy it on a modified environment featuring two randomly placed objects: a yellow star and a red gem; the agent is forced to choose between consistency in shape or in color (Figure 3). Except for occasionally getting stuck in a corner, the agent almost always successfully pursues the yellow star, thus generalizing in favor of color rather than shape consistency. When there is no straightforward generalization of the training reward, the way in which the agent’s objective will generalize out-of-distribution is determined by its inductive biases.
3.3 Keys and Chests

So far, our experiments featured environments in which there is a perfect proxy for the true reward. The Keys and Chests environment, first suggested by Barnett [6], provides a different type of example. This environment, which we implement by adapting the Heist environment from Procgen, is a maze with two kinds of objects: keys and chests. Whenever the agent comes across a key it is added to a key inventory. When an agent with at least one key in its inventory comes across a chest, the chest is opened and a key is deleted from the inventory. The agent is rewarded for every chest it opens.

The objective robustness failure arises due to the following distributional shift between training and test environments: in the training environment, there are twice as many chests as keys, while in the test environment there are twice as many keys as chests. The basic task facing the agent is the same (the reward is only given upon opening a chest), but the circumstances are different.

We observe that an agent trained on the “many chests” distribution goes out of its way to collect all the keys before opening the last chest on the “many keys” distribution (Figure 4), even though only half of them are even instrumentally useful for the true reward; occasionally, it even gets distracted by the keys in the inventory (which are displayed in the top right corner) and spends the rest of the episode trying to collect them instead of opening the remaining chest(s). Applying the intentional stance, we describe the agent as having learned a simple behavioral objective: collect as many keys as possible, while sometimes visiting chests. This strategy leads to high reward in an environment where chests are plentiful and the agent can thus focus on looking for keys. However, this proxy objective fails under distributional shift when keys are plentiful and chests are no longer easily available.

4 Related Work

Learned optimization The main inspiration for this paper is the work of Hubinger et al. [18] on learned optimization. Its premise is that for many tasks, the simplest way to solve them is to perform search according to an objective function (e.g. to perform well at chess, an agent must search through possible moves and evaluate them). This leads to a problem: when ML systems learn to perform search according to an objective, how do we make sure that the learned objective is equivalent to the training objective, even out-of-distribution? If many complex tasks require learning a planner+objective, then solving this problem would be crucial for applying deep learning systems to difficult real-world problems.

We do not focus on the alignment of learned optimizers, though it is certainly a noteworthy special case of objective robustness. Instead, we study objective robustness more generally, and provide the first (to our knowledge) explicit empirical demonstrations of objective robustness failures.
Figure 4: Objective robustness failure on the "keys and chests" task. The agent must collect keys in order to open chests and is only rewarded for opening chests. **Left:** The agent is trained on procedurally generated mazes in which there are twice as many chests as keys. **Right:** At test time, there are instead twice as many keys as chests. The agent more highly values collecting keys than opening chests; it routinely goes out of the way to collect all the keys before opening any remaining chests despite the fact that doing so offers no benefit to its actual return (in fact, it would decrease its time-discounted return).

**Objective robustness** Recent work has introduced and discussed the concept of objective robustness. Though they do not use the term, Leike et al. [25] refer to the difference between what a model was optimized for and what it appears to be optimizing as the reward-result gap. A related distinction is made by Mikulik [26] between 1) robustness failures in which a model fails to generalize capably and 2) those in which a model generalizes capably but pursues a different objective than the one on which it was trained. The term **objective robustness** is then introduced by Hubinger [16] to refer to the latter failure mode. These works collectively identify a type of robustness failure that is qualitatively distinct from the kind usually studied in the literature (where models perform poorly out-of-distribution because they did not learn general enough capabilities). To our knowledge, we are the first to empirically study objective robustness.

**Reward misspecification** Reward specification is the problem of specifying a reward that captures the behavior we want [2,9]. Objective robustness is a distinct problem: it may still fail even if the reward function is perfectly specified.

**Adversarial Robustness** Adversarial examples are a well-known kind of capability robustness failure. In image classification, adversarial examples are typically found by optimizing small $l_p$ norm perturbations to images to cause misclassification, despite the changes being imperceptible to humans [35,14,13]. More recent works argue that real-world attackers are not limited to small perturbations [11] and that the norm-perturbation model is only a useful local approximation to the true worst-case risk [57]. For these reasons, Brown et al. [8] introduced a contest to evaluate ML systems against unconstrained (as opposed to norm-constrained) adversaries. In reinforcement learning, agents have also been shown to be vulnerable to small perturbations on input images [15,21], as well as vulnerable to adversarial policies: policies that attack the agent simply by taking actions in the same environment and thereby modifying the agent's observations to cause poor performance [12].

**Out-of-Distribution Robustness** Adversarial examples and objective robustness failures are types of OOD robustness failures; in OOD robustness, the goal is to optimize worst-case performance over a perturbation set of possible test domains (environments) $F$. As in the case of adversarial examples [19], the reason why ML models usually fail OOD in general is that they tend to learn features that are highly predictive on the training domain(s) but are brittle to distributional shift, also known as spurious correlations. Causes for this type of train-test mismatch (non-exhaustively) include 1) the training data does not characterize the true distribution [56], 2) the distribution shifts over time

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3 Failures due to objective misspecification, occur when the model behaves in an unintended way that nevertheless scores highly on the reward function. In contrast, in failures of objective robustness, models score poorly on the training reward because they are pursuing an different objective.
and 3) the training or the test data are adversarially perturbed (as in the case of adversarial examples, discussed above). Approaches that address OOD robustness include learning causally invariant representations \[5], \[22]\ and, in the case of label noise, modifying the training objective \[30].

The existing work on OOD robustness is largely complementary to our work here on objective robustness. For example, the work of Arjovsky et al. \[5]\ and Krueger et al. \[22]\ indicate that one approach that might alleviate objective robustness failures is learning invariant representations across a sufficient diversity of environments, which could help the model learn the true causes leading to it receiving the reward. Our CoinRun ablation over how often the coin is randomly placed in training (Section \[3.1.1]) also indicates that training with greater environmental diversity can help identify the true objective. Overall, the OOD robustness literature indicates that models tend to misgeneralize because they learn spurious correlations. The distinction between capability and objective robustness highlights that when a model fails to generalize due to learning spurious correlations, it may do so in two different ways that have notably different consequences: it might generalize completely incapably, or it might generalize capably but pursue an incorrect objective.

**Unidentifiability** Objective robustness failures tend to arise when there are multiple possible reward functions that are indistinguishable from the true reward. This type of unidentifiability is analogous to the one encountered in inverse reinforcement learning (IRL). In their seminal paper on IRL, Ng and Russell \[28]\ note that identifying the exact reward function an optimal agent optimizes with its behavior is in general impossible since there may be infinitely many reward functions consistent with any observed policy \(\pi\) in a fixed environment. Amin and Singh \[1]\ separate the causes for this unidentifiability into two classes: *representational unidentifiability*, where a set of reward functions is behaviorally invariant under certain arithmetic operations (e.g., re-scaling), and *experimental unidentifiability*, where \(\pi\)’s observed behavior is insufficient to distinguish between two or more reward functions which both rationalize the behavior of the agent (the behavior is optimal under both); they also demonstrate that experimental unidentifiability can be alleviated if the agent can be observed in other MDPs with different transition dynamics. In the context of objective robustness, the reward function is unidentifiable by the agent. Given a history of trajectories and rewards in the training environment(s), many possible reward functions fit the data that will generalize OOD differently; this is analogous to experimental unidentifiability.

5 Discussion

In summary, we provide concrete examples of reinforcement learning agents that fail in a particular way: their capabilities generalize to an out-of-distribution environment, whereupon they pursue the wrong objective. While deep RL practitioners may generally be aware that this type of failure is possible, there has not yet been much discussion of objective robustness as distinct from other types of out-of-distribution robustness. We argue that objective robustness is a natural category since, much like adversarial robustness failures, objective robustness failures have distinct causes and pose distinct problems. By introducing the objective robustness problem to a broader audience, we hope to spark interest in it as an avenue for future research.

Additionally, there is much space for further empirical work on the factors that might influence the likelihood of objective robustness failures described in Section \[2.2]. For instance, what kinds of proxy objectives are agents most likely to learn? A better understanding here could inform the choice of an adequate perturbation set over environments to enable the training of objective robust models. Scaling up the study of objective robustness failures to more complex environments than the toy examples presented here should also facilitate a better understanding of the kinds of behavioral objectives our agents are likely to learn in real-world tasks.

Finally, a more rigorous and technical understanding of the concept of the behavioral objective seems obviously desirable. In this paper, we understood it more informally as equivalent to a goal or objective under the intentional stance \[10]\ because humans already intuitively understand and reason about the intentions of other systems through this lens and because formally specifying a behavioral definition of objectives or goals fell outside the scope of this project. However, a more rigorous definition could enable the formalization of properties we could try to verify in our models with e.g. interpretability techniques.
5.1 Limitations

- Our experiments demonstrate the existence of objective robustness failures and illustrate some of their causes; they do not prove that they will occur in problems of interest. We do however think that there are good arguments for this (Section 2.2).
- The notion of objective robustness is quite recent. With time, the objective vs. capability robustness distinction may be superseded by a categorization that better captures the problems that occur in practice, is more grounded in theory, or both. However, it seems clear that there are different kinds of possible robustness failures, and understanding how they differ in their causes and consequences is important for building safe and capable AI systems.

Broader Impact

Our motivation in writing this paper was to address a failure mode in deep reinforcement learning systems that we see as particularly concerning. Highly capable agents taking actions in the service of misaligned objectives could be catastrophic when deployed in the real world. Our hope is that making this risk more tangible with concrete demonstrations of objective robustness failures in modern systems in relatively simple environments will spark further research into both the problem and the space of potential solutions. Ensuring that our systems have actually the objectives we want them to is critical for being able to usefully deploy AI in the world.

We therefore expect research into objective robustness to have a robustly beneficial impact in general. One scenario where this might fail to be true is if a better understanding of objective robustness failures makes it easier to purposefully induce such failures. Perhaps adversaries could induce a distributional shift where an agent’s behavioral objective comes apart from the training objective.

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A Hyperparameters

We use the Adam optimizer [20] in all experiments.

Table 1: PPO Hyperparameters

| ENV. DISTRIBUTION MODE | HARD |
|------------------------|------|
| γ                      | .999 |
| λ                      | .95  |
| LEARNING RATE          | 0.0005 |
| # TIMESTEPS PER ROLLOUT | 256  |
| EPOCHS PER ROLLOUT     | 3    |
| # MINIBATCHES PER EPOCH | 8    |
| MINIBATCH SIZE         | 2048 |
| ENTROPY BONUS ($k_H$)  | .01  |
| PPO CLIP RANGE         | .2   |
| REWARD NORMALIZATION?  | YES  |
| LEARNING RATE          | $5 \times 10^{-4}$ |
| # WORKERS              | 4    |
| # ENVIRONMENTS PER WORKER | 64   |
| TOTAL TIMESTEPS        | 200M |
| ARCHITECTURE          | Impala |
| LSTM?                  | No   |
| FRAME STACK?           | No   |