Shielding Atari Games with Bounded Prescience

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ABSTRACT

Deep reinforcement learning (DRL) is applied in safety-critical domains such as robotics and autonomous driving. It achieves super-human abilities in many tasks, however whether DRL agents can be shown to act safely is an open problem. Atari games are a simple yet challenging exemplar for evaluating the safety of DRL agents and feature a diverse portfolio of game mechanics. The safety of neural agents has been studied before using methods that either require a model of the system dynamics or an abstraction; unfortunately, these are unsuitable to Atari games because their low-level dynamics are complex and hidden inside their emulator. We present the first exact method for analysing and ensuring the safety of DRL agents for Atari games. Our method only requires access to the emulator. First, we give a set of properties that characterise "safe behaviour" for several games. Second, we develop a method for exploring all traces induced by an agent and a game and consider a variety of sources of game non-determinism. We observe that the best available DRL agents reliably satisfy only very few properties; several critical properties are violated by all agents. Finally, we propose a countermeasure that combines a bounded explicit-state exploration with shielding. We demonstrate that our method improves the safety of all agents over multiple properties.

1 INTRODUCTION

Deep reinforcement learning (DRL) combines neural network architectures with reinforcement learning (RL) algorithms and, capitalising on recent advances in both technologies, has been successfully employed in many areas of artificial intelligence, from playing games against humans to controlling robots in the physical world [13, 36, 41]. A setup of this kind consists of an agent, a neural network, that automatically learns to control the behaviour of the environment by maximizing rewards received as consequence of its actions. DRL has demonstrated super-human capabilities in numerous applications, notably, the game of Go [36]. DRL is now used in safety-critical domains such as autonomous driving [26]. While DRL agents perform well most of the time, the question of whether unsafe behavior may occur in corner cases is an open problem. Safety analysis answers the question of whether the environment can possibly steer the system into an undesirable state or, dually, whether the agent is guaranteed to remain within a set of safe states (an invariant) in which nothing bad happens [11, 15, 27]. We discuss the safety of popular DRL methods for one of the most challenging benchmark environments: the Atari 2600 console games.

Games for the classic Atari 2600 console are environments with low-resolution graphics and small memory footprints, which are simple when compared with contemporary games, yet offer a broad variety of scenarios including many that are difficult for modern AI methods [4, 28, 30, 39]. Macroscopically, diversity in the game mechanics challenges the generality of the machine learning method; microscopically, diversity in the outcome for multiple identical plays, i.e., the non-determinism in the game, challenges the robustness of the trained agent. Many Atari games exploit variations in the response time of the human player for differentiating runs and, in some cases, for initializing the seeds of random number generators. The Arcade Learning Environment (ALE), i.e., the framework upon which the OpenAI gym for Atari is built, introduces non-determinism by randomly injecting no-ops, skipping frames, or repeating agent actions [18, 28]. On one hand, this prevents over-fitting the agent but, on the other hand, implies that there is no guarantee that an agent works all of the time—the scores that we use to rank training methods are averages. Agents are trained for strong average-case performance.

The application of DRL in safety-critical applications, by contrast, requires worst-case guarantees, and we expect a safe agent to maintain safety invariants. To evaluate whether or not state-of-the-art DRL delivers safe agents we specify a collection of properties that intuitively characterize safe behaviour for a variety games, ranging...
from generic properties such as “don’t lose lives” to game-specific ones such as avoiding particular obstacles. Figure 1 illustrates the property “duck avoids cars” in the game Freeway. In the scenario in Fig. 1a this property is maintained regardless of the action chosen by the agent whereas the scenario given in Fig. 1b offers the possibility of violating it. We conjecture that satisfying our properties is beneficial for achieving a high score, and therefore study whether neural agents trained using best-of-class DRL methods learn to satisfy these invariants. Finally, we discuss a countermeasure for those that violate them.

The safety of DRL has been studied from the perspective of verification, which determines whether an trained agent is safe as-is [22], and that of synthesis, which alters the learning or the inference processes in order to obtain a safe-by-construction agent [11]. Verification methods for neural agents have borrowed from constraint satisfaction or abstract interpretation [5, 12, 25]. Both approaches are symbolic and, for this reason, require a symbolic representation not only for the neural agent but also for the environment. They have been used for reasoning about neural networks in isolation, e.g., image classifiers [22, 22], or for environments whose dynamics are determined by symbolic expressions, e.g., differential equations [22, 40]; unfortunately, they are unsuitable to Atari games because their mechanics are hidden inside their emulator, Stella, i.e., the core of ALE. For this reason, we adopt an explicit-state verification strategy and then, building upon it, we construct safe agents.

We introduce a novel verification method for neural agents for Atari games. Our method explores all reachable states explicitly by executing, through ALE, the games and agents and labels each state for whether it satisfies our properties. More precisely, we enumerate all traces induced by the non-deterministic initialisation of the game and label states using their lives count, rewards, and the screen frames generated, which allows us to specify 43 non-trivial properties for 31 games. We compare agents trained using different technologies, i.e., A3C [29], Ape-X [20], DQN [31], IQN [9], and Rainbow [19], and observe that all of them violate 24 of our properties, whereas only 4 properties are satisfied by all. Surprisingly, properties that are intuitively difficult for humans, e.g., not dying, are satisfied by some agents, whereas many that we judge as simple, e.g., keeping a gun from overheating in game Assault, are violated by all agents. To improve the overall safety of neural agents wrt. our properties, we employ our explicit-state labelling and exploration technique to shielding neural agents.

Ensuring safety amounts to constraining the traces of the system within those that are admissible by the safety property. Methods that act on the training phase modify the optimization criterion or the exploration process in order to obtain neural agents that naturally act safely [11]. Methods of this kind typically require known facts about the environment for providing guarantees and have not been applied to Atari games, or exploit external knowledge (e.g., teacher advice) [35]. On the other side of the spectrum, shielding enables the option of fixing unsafe agents at inference phase only, introducing a third actor—the shield—that takes over control when necessary and with minimal interference [1, 23, 24]. A shield is constructed from a safety property in temporal logic and a model of the environment or an abstraction. Leveraging the fact that the safety property is usually easy to satisfy in contrast to the main objective, shielding is efficient with respect to training for safety. However, complete models for Atari games are not available and abstractions are hard to construct automatically; for this reason, we adapt shielding to our exploration method.

We study the effect of shielding DRL agents from actions that lead to unsafe outcomes within some bounded time in the future. For this purpose, we augment agents with shields that, during execution, restrict their actions to those that are necessarily safe within the prescience bound. Before taking an action, our bounded-prescience shield (BPS) enumerates all traces from the current state for a bounded number of steps and labels each of them as safe or unsafe using our verification technique; then, it invokes the agent and chooses the next action whose traces are all labelled as safe and whose agent score is the highest. As a result, we fixed all violated properties that we deemed as simple using BPSs with shallow prescience bounds of 3 steps. Notably, we also fixed the properties that we consider non-trivial and that were satisfied by most non-deterministic executions under the original agent. Overall, BPS demonstrated its effectiveness for those properties that are simple yet always violated by the original agents, or those that are difficult yet were almost satisfied.

Summarising, our contribution is threefold. First, we enrich the Atari games with the first comprehensive library of specifications for studying RL safety. Second, we introduce a novel technique for evaluating the safety of agents based on explicit-state exploration and discover that current DRL algorithms consistently violate most of our safety properties. Third, we propose a method that, exploiting bounded foresight of the future, has mitigated the violation of a set of simple yet critical properties, without interfering with the main objective of the original agents. To the best of our knowledge, our method has produced the safest DRL agents for Atari games currently available.

2 SAFETY FOR ATARI GAMES

In this section we discuss ALE [28], which is a tool for running Atari 2600 games based on the Stella emulator. While any of the hundreds of available Atari games can be loaded into the emulator, ALE provides built-in support for 60 games and those are generally the ones studied. This set of games contains a wide variety of different tasks and dynamics.

2.1 Markov Decision Processes

We focus on the standard formalisation of sequential decision-making problems, i.e., Markov decision processes (MDP), which assumes that the actions available, the rewards gained and the transition probabilities only depend on the current state of the environment and not the execution history. Formally, an MDP is given as a tuple $M = (S, s_0, A, P, R)$, where $S$ is the set of states of the environment, $s_0$ is the initial state, and $A$ is the set of actions. The dynamics of the environment are described by $P : S \times A \times S \rightarrow [0, 1]$, where $P(s, a, s')$ is the probability of transitioning to $s'$ given the agent chooses action $a$ in state $s$. The obtained reward when action $a$ is taken in a given state $s$ is a random variable $R(s, a) \sim \rho(s, a) \in \mathcal{P}(\mathbb{R})$, where $\mathcal{P}(\mathbb{R})$ is the set of probability distributions on subsets of $\mathbb{R}$, and $\rho$ is the reward distribution. A possible realisation of $R$ is denoted by $r$ [33].
Partially observable Markov decision processes (POMDPs) are general cases of MDPs, and Atari games can perhaps be most naturally modelled as a POMDP. When defining a POMDP, the MDP tuple $M = (S, S_0, A, P, R)$ is extended with a set of observations $\Omega$ and a conditional observation probability function $O : S \times A \times \Omega \rightarrow \mathbb{R}$. When picking an action $a$ in state $s$, the agent cannot observe the subsequent state $s'$ but instead receives an observation $o \in \Omega$ with probability $O(o|s', a)$. Unlike when using MDPs one cannot assume that an optimal policy for a POMDP will depend only on the last observation—in fact, effective use of memory is often crucial. Further, we assume that the state-space $S$ includes a “terminating state”.

In an Atari game the full state $s \in S$ is given by a valuation of the 128-byte RAM, along with a set of registers and timers. There is no additional screen buffer, which means an observation $o \in \Omega$ is given by a $210 \times 160$ display frame, which is computed deterministically from the state $s$. ALE executes the Atari games using the Stella emulator, and treats this emulator almost entirely as a black-box. The only manipulation ALE carries out during the run of a game is sending the control input selected by the agent to the emulator, reading the screen and reading two fixed memory addresses where the score (used as the reward signal) and the current number of lives are stored. There are a total of 18 discrete actions possible in any state, including “no operation”. The Atari games are all deterministic. This essentially means that the above POMDP is easily convertible into an MDP where at each time step $t$, the MDP state $s_t$ is a finite sequence of observations and actions, i.e. $s_t = o_0, a_0, o_1, a_1, \ldots, o_t, a_t$. This formalization gives rise to a large but finite MDP.

### 2.2 Safety Properties

Traditionally the reward signal exposed by ALE is used as the only measure of success. In order to study to which degree the behavior of trained agents is safe, we hand-engineer a suite of 43 safety properties across 30 games, which identify unsafe states of the MDP. The choice of the properties is highly subjective. The authors believe that all properties should be satisfied at all times by a highly reliable and robust agent.

We observe that some of the properties are easy to satisfy whereas others require near perfect gameplay. Consider the Atari game Bowling. The property Bowling:no-strike identifies any state in which the player fails to score a strike as unsafe. We also include “not losing lives” as a property in all games where it applies, and this property can also be highly challenging in many games. To better interpret the results we identify two distinct sets of properties that we consider “easy” and “hard”.

#### 2.2.1 Shallow Properties.

We say that a property is shallow if violations of the property are always caused by recent actions (within 10 frames or fewer). More precisely, for any unsafe state encountered during a trace, there should be a previous state at most 10 frames earlier in the trace from which a safe strategy exists. In Assault, the player loses a life from overheating if they overuse their weapon in a short timespan. The property Assault:overheat marks states where such an overheating happens as unsafe. This is an example of a shallow property, since “not firing” is always a safe strategy starting from the frame just before overheating (such a frame is given in Figure 2). Another example is the game DoubleDunk, where the player is penalised for stepping outside of the field. This violates the property DoubleDunk:out-of-bounds, and whenever a violation occurs, simply moving in the opposite direction a few frames back would have avoided the violation.

Ensuring the safety of shallow properties does not require long-term planning. It is reasonable to expect that most agents will satisfy all shallow properties.

#### 2.2.2 Minimal Properties.

We say that a property is minimal if satisfying it is a necessary requirement for scoring at least 10% of the human reference level. Violating any of these properties would indicate a complete inability to play the game, and yield a near-zero or negative score. An example is Bowling:no-hit, which marks states where all pins are missed as unsafe. We observe that while most minimal properties are usually “easy”, they are not necessarily shallow as can be seen in Figure 3. By the time the miss occurs the throw that caused it happened hundreds of frames in the past.
3 DEEP RL ALGORITHMS

It has been shown [7, 33] that in any MDP $\mathcal{M}$ with a bounded reward function and a finite action space, if there exists an optimal policy, then that policy is stationary and deterministic, i.e. $\pi : S \rightarrow A$. A deterministic policy generated by a DRL algorithm is a mapping from the state space to action space that formalises the behaviour of the agent whose optimisation objective is

$$\mathbb{E} \left[ \sum_{t=0}^{\infty} y^t R(s_t, a_t) \right],$$

where $0 < y \leq 1$ is the discount factor, and the goal is to find a policy, call it $\pi^*$, that maximises the above expectation.

This paper focuses on model-free RL due to its success when dealing with unknown MDPs with complex dynamics including Atari games [31], where full models are difficult to construct. A downside of model-free RL however is that without a model of the environment formal guarantees for safety and correctness are often lacking, motivating the work on safe model-free RL [15]. A classic example of model-free RL is Q-learning (QL) [42], which does not require any access to the transition probabilities of the MDP and instead updates an action-value function $Q : S \times A \rightarrow \mathbb{R}$ when examining the exploration traces. While vanilla model-free RL, e.g. QL, avoids the exponential cost of fully modelling the transition probabilities of the MDP, it may not scale well to environments with very large or even infinite sets of states. This is primarily due to the fact that QL updates the value of each individual state-action pair separately, without generalising over similar state-action pairs. To alleviate this problem one can employ compressed approximations of the $Q$-function. Although many such function approximators have been proposed [3, 6, 10, 32, 38] for efficient learning and effective generalisation, this paper focuses on a particular representation, which has seen much success in recent years: neural networks [21].

Neural networks with appropriate activation functions are known to be universal function approximators when given enough hidden units [8, 21]. Thus, the use of DNNs with many hidden layers requires only few assumptions on the structure of the problem and consequently introduces significant flexibility into the policy. More importantly, it has been shown empirically that despite being severely overparametrised, neural networks seem to generalise well if trained appropriately. This, along with efficient algorithms for fitting networks to data through backpropagation, has made the use of DNNs widespread. In RL this has led to the paradigm of DRL [2].

The performance of DRL when applied to playing Atari 2600 games using raw image input led to a surge of interest in DRL [31]. The $Q$-function in [31] is parameterised $Q(s, a|\theta)$, where $\theta$ is a parameter vector, and stochastic gradient descent is used to minimise the difference between $Q$ and the target estimate and by minimizing the following loss function:

$$L(\theta) = \mathbb{E}_{(s,a,r,s') \sim \mathcal{U}} \left[ (r + y \max_{a' \in A} Q(s', a'|\theta) - Q(s, a|\theta))^2 \right].$$  \hspace{1cm} (1)

Actions and states are sampled by letting the agent explore the environment. The experience data points $(s, a, r, s')$ are stored in a replay buffer $\mathcal{U}$, as in vanilla QL. Generally this pool of experiences is capped at a certain size at which point old ones cycle out. This means the training objective evolves only gradually and additionally ensures that individual experiences are more independent rather than always being consecutive, reducing the variance in training. This however exposes an important difference to regular supervised learning, where the updates that are made to the $Q$-function change the distribution of data, and thus also the training objective. This means training the neural network to correctly estimate $Q$-values given the current policy has to be interleaved with gathering new data by letting the agent interact with the environment.

Convergence of neural-network-based methods is in general much less certain than it is for QL that uses a look-up table. There are many other methods for DRL that are not closely based on QL. In particular, there are policy gradient approaches that do not attempt to estimate the value of states but rather directly fit policy parameters to maximise rewards. The common aspect of these methods is that they scale well to large and complex problems, but in turn are often opaque and lack theoretical convergence guarantees.

We gathered 29 state-of-the-art DRL algorithms for Atari games to find the policies that achieve the best performance across all games:

- We include all algorithms whose implementations are available for ALE [28] or OpenAI Gym [4].
- We consider every algorithm that achieved a top five score on any of the OpenAI Gym leader-boards\(^1\).
- We additionally include algorithms that are prominently benchmarked against other works.

We ranked the algorithms by the number of games in which they placed among the top 5 of the 29 total gathered Atari algorithms. To avoid mistakes in training from affecting our assessment we then restricted the search to algorithms for which benchmarked pretrained agents were available. This ultimately gave us the list of top performing available algorithms: Ape-X [20], A3C [29], IQN [9], and Rainbow [19]. We also included the traditional DQN [31] for comparison. Figure 4 shows the average normalised rewards $R_n$ over all games for each algorithm in our testing where

$$R_n = \frac{100 \times \frac{R - R_r}{R_h - R_r}}{R_h - R_r},$$

where $R_r$ is the average reward of a random agent, and $R_h$ a recorded average of human play [31]. We use a shorter episode length (5 min.) than that used in [31] to be able to run more traces, so the result is not directly comparable (e.g. 100% is above human level, since it is

\(^1\)https://github.com/openai/gym/wiki/Leaderboard
accomplished in less time). We still apply the normalisation since the purpose is not to compare with humans or other studies but to normalise the relative impact of each game within our study.

The main question is whether these top performing algorithms are able to satisfy safety properties that are obviously desirable to a human player.

4 SAFETY ANALYSIS VIA EXPLICIT-STATE EXPLORATION

We are interested in proving invariant safety properties, i.e., we want to show that the synthesised policy never enters a state that is labelled ‘unsafe’. The definition of a property thus boils down to defining a set of unsafe states, or equivalently its complement, a set of safe states. Let \( \varphi \) be a safety property whose labelling function is denoted by \( L_\varphi : S \rightarrow \{\text{safe}, \text{unsafe}\} \). With \( s_0 \) being the starting state of the Atari game, we define \( s_{i+1} = P(s_i, \text{no-op}) \) as the sequence of states achieved by repeatedly performing the ‘no-op’ action. We then have \( I = \{s_i | i < v\} \) as the set of initial states from which an action selection policy \( \pi \) is followed. We assume the state-space \( S \) contains a terminating state \( \bot \), which is always labelled safe.

To verify \( \varphi \), i.e. that the system will never enter an unsafe state, we simply need to check whether any reachable state has label ‘unsafe’. Given that all the games and the agents are deterministic except for having multiple starting states we can simply follow the deterministic path starting at each initial state \( s \in I \) until we reach the terminating state, from which no other state is reachable. We record if the labelling function associated with \( \varphi \) reports ‘unsafe’ for any state on the path.

4.1 Non-determinism in Atari Games

One of the more difficult aspects of training and evaluating models on Atari is appropriately handling non-determinism. The dynamics within each game are entirely deterministic, other than the initialisation behaviour, which depends on an adjustable seed. The Stella emulator very closely emulates the original hardware and also performs random RAM initialisation using a seed that is derived from the system clock. In order to bring back some of the intended randomness of the original games, and also to create a more interesting training environment that requires some level of generalisation, ALE introduces additional forms of stochastic behaviour. Since the environments in ALE are treated in a black-box manner this is done purely through modifying the actions selected by the policy. Some of the most common ways of introducing stochasticity include:

- **No-ops**, where ALE sends a random number between 0 and 30 of no-operation actions at the start of the game, both letting the environment evolve into a random starting state and randomly seeding the game.
- **Sticky actions**, where a random chance (often 25\%) of repeating the previous action is introduced every frame. This in some sense mimics a human’s imperfect frame timing, since a human player is not able to trigger an action in sync with a particular frame reliably.
- **Frame skips**, where each action is repeated a random number of times, e.g. in OpenAI Gym [4] the default is between 3–5 times. This is very similar to sticky actions, but with a different probability distribution over number of times the action is repeated. Importantly, frame-skips have finite support, e.g. with Gym-style frameskips there is an equal \( \frac{1}{5} \) probability of 3, 4 or 5 repeats and no chance of any other number, whereas sticky actions can in theory lead to repeating the action an arbitrary number of times before giving back control to the policy.
- **Human starts**, which is a more elaborate version of the no-ops start where ALE sends a memorised series of commands based on a human trace before handing over control to the policy.

Each method has distinct advantages and disadvantages. No-ops and also human starts randomise over a certain fixed number of starting conditions [18, 28] while ALE and OpenAI Gym adopted sticky actions and frame skips respectively.

4.2 Labelling Functions

The labelling function \( L_\varphi \) can be defined as a mapping directly from the underlying machine state (RAM). However, as stated before, correctly interpreting the RAM to define even simple properties proved to be difficult. We thus use the history of actions, video frames, the life counter and rewards as the state passed to the labelling functions instead. We categorise the labelling functions into three classes:

- **Life-count Labelling**: A common safety property that is used across many games is simply avoiding losing a life or \( \varphi = \text{dying} \). For games where there is a life counter, the Atari 2600 emulator returns the number of lives left in the game [28]. A labelling function for these properties is easy to define. Namely, the labelling function labels a state unsafe if the life counter reported by ALE is reduced compared to the previous state.
- **Reward-based Labelling**: Another set of labelling functions are those that are directly induced from the game score. For instance, a safety property in Boxing is ‘not to get knocked out’ \( \varphi = \text{no-enemy-ko} \); the agent gets knocked out if the opponent scores 100 hits on the agent. Since there is no other way of losing score, a function that only accumulates the total negative reward labels a state as unsafe once \(-100\) is reached. Many other properties can be derived from the reward through various schemes similar to Boxing.
- **Pixel Image Labelling**: Some safety properties however do not correspond clearly to any specific reward or life-loss signal. For instance, \( \varphi = \text{overheat} \) in Assault results in the exact same punishment as dying, however avoiding overheating represents a distinct and easier behaviour than avoiding death in general. To label such properties we process raw RGB frames and examine pixels of specific colours in specific places, or track the position of objects on the screen. The simplistic graphics of the Atari 2600 makes the image processing and labelling real-time. However, this type of labelling functions requires by far the most work and is also most prone to mistakes.

4.3 Safety Analysis Results

We initialise each game with \( \nu = 30 \) rounds of no-ops of different length; each round produces a different initial state. For each of
these initial states, we run the game together with the agent and recorded whether an unsafe state was eventually reached and, if so, how many steps it takes. Additionally, we record the total reward achieved by the policy over the trace. As a result, for each game we obtain whether it satisfies the property, that is all traces satisfy it, or additionally measured the degree of safety, determined by the ratio of satisfying traces over all traces.

Overall we run 301 analyses, 43 for each of the 7 algorithms, out of which 72 show an agent satisfying a safety property. Figure 5 gives the performance of the agent trained by each algorithm with respect to the properties it could satisfy. Notably, IQN yields the largest number of safe traces, followed by A3C in second and Ape-X in third place.

The degree of safety correlates well with the reward obtained, as we show in Fig. 6. Despite this good correlation between the average reward and safety, all of the algorithms violate at least some safety properties across all the games. In absolute terms, no algorithm achieves a 50% safety score. This essentially means that maximising the reward is not equivalent to acting safe, and it is clear that the algorithms considered do not reliably learn safe behaviour. By inspecting individual traces, it often appears that the agents are capable of satisfying the safety properties, meaning that there exist examples among the traces of the agent in which the agent correctly dealt with complex situations with high risk of violating the safety property. But the reward structure or perhaps just insufficient training means it lacks reliability and robustness, and sometimes fails even in simple situations.

Furthermore, there are still noticeable differences between the trained agents, both comparing ones trained using different learning algorithms, and those which only differed in implementation, e.g. DQN Atari-Zoo and ChainerRL. This provides further evidence that the safety of these methods depends on various contingent, opaque and poorly understood factors. In what follows we examine the properties are satisfied and violated by the agents in more detail, with a view towards improving their safety.

To determine how agents behave with respect to our properties, we study the distribution of traces satisfied by each of them. Figure 7 illustrates how many analyses ended with all 30 runs satisfying the property, no runs satisfying the property, and everything in between. Notably, IQN yields the largest number of safe traces, followed by A3C in second and Ape-X in third place.

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To determine how agents behave with respect to our properties, we study the distribution of traces satisfied by each of them. Figure 7 illustrates how many analyses ended with all 30 runs satisfying the property, no runs satisfying the property, and everything in between. Notably, most outcomes are distributed in the extreme cases, which indicates that statistically agents either satisfy a property or they don’t. Only a small amount of cases are close to satisfaction or close to violation. This indicates that our safety properties are robust and insensitive to any non-deterministic noise emerging from the combination of game and agent.

Most of our properties are consistently violated. Figure 8 shows that 24 out of 43 of our properties are violated by all agents. On the other side, only 4 properties are satisfied by all and 3 out of 4 of these properties are classified as minimal. Minimal properties are not easy yet essential for making progress in the game. Training algorithms optimize for reward and, indirectly, for progress
and therefore they satisfy minimal properties as a side effect. This indicates that reward functions focus on progress but are incomplete with respect to safety. Three shallow properties, which are properties that are simple to satisfy, are not satisfied by all agents and one in particular is violated by all. These violations should be avoidable with a shallow exploration of the future. We investigate this hypothesis in the next section.

5 BOUNDED-PRESCIENCE SHIELDING

Standard safe policy synthesis in formal methods requires full knowledge of environment dynamics or the ability to construct an abstraction of it [34, 37, 43]. In practice, however, the dynamics are not fully known, and abstractions are too hard to compute.

RL and DRL methods address the computational inefficiency of safe-by-construction synthesis methods, but on the other hand cannot offer safety guarantees [14, 16]. This issue becomes even more pressing when the learning algorithm entirely depends on non-linear function approximation to handle large or continuous state-action MDPs [17, 18]. For instance, the loss function (1) in DRL and consequently the synthesised optimal policy \( \pi^* \) only accounts for the expected reward.

The concept of shielding combines the best of two worlds, that is, formal guarantees for a controller with respect to a given property and policy optimality despite an environment that is unknown a priori [1, 23, 24]. The general assumption is that the agent is enabled to observe the MDP and the actions of any adversaries to the degree necessary to guarantee that the system remains safe over an infinite horizon.

In this work, we propose a new technique we call BPS, which only requires observability of the MDP up to a bound \( H \in \mathbb{N} \). This relaxes the requirement of full observability of MDP and adversaries and more importantly, allows the shield to deal with MDPs with large state and action spaces. In particular, we will show that BPS is an effective technique for ensuring safety in Atari games where the MDP induced by the game is hard to model or to abstract (Section 2).

A finite path \( \rho = (s, a) \) starting from \( i \) is a sequence of states and actions

\[
\rho = s_0 \xrightarrow{a_0} s_1 \xrightarrow{a_1} \ldots \xrightarrow{a_{n-1}} s_n
\]

such that every transition \( s_i \xrightarrow{a_i} s_{i+1} \) is allowed in MDP \( M \), i.e., \( P(s_i, a_i, s_{i+1}) > 0 \) and \( s_n \) is a terminal state. A bounded path of length \( L \) is a path with no more than \( L \) states, where either the final state \( s_n \) is terminal or the number of states is exactly \( L \). We denote the set of all finite paths that start at an arbitrary state \( s_p \in S \) by \( \varrho(s_p) \), and the set of all bounded finite paths of length \( L \) that start at \( s_p \) by \( \varrho_L(s_p) \).

Given a safety property \( \varphi \), a (bounded) finite path \( \rho \) is called safe with respect to \( \varphi \), written \( L_\varphi(\rho) = 1 \), if

\[
L_\varphi(s_i) = \text{safe} \ \forall s_i \in \rho,
\]

where \( L_\varphi : S \rightarrow \{ \text{safe}, \text{unsafe} \} \) is the labelling function of the safety property \( \varphi \). A policy \( \pi \) is safe with respect to a property \( \varphi \) if for any state \( s_0 \),

\[
\exists \rho = (s, a) \in \varrho(s_0) \left( L_\varphi(S(\rho, \varphi) \land \pi(s_0) = a_0) \lor \forall \rho \in \varrho(s_0) (\neg L_\varphi(S(\rho, \varphi)) \right)
\]

(2)

or in other words if the policy always picks an action that starts a safe finite path if one exists. Finally, a policy is bounded safe with bound \( H \) with respect to \( \varphi \) if Equation 2 is satisfied when replacing "finite paths" by "bounded paths of length \( H \”).

Our shield modifies the policy \( \pi \) of the trained agent to obtain a policy \( \pi' \) that is guaranteed to satisfy bounded safety. This is done by forward-simulating \( H \) steps and forbidding actions that cannot be continued into a safe bounded path of length \( H \). Where the policy has preferences among available actions we pick the most preferred one that starts some safe bounded path. This is the case for all our DRL agents, whose final layer expresses all preferences. If none of the available actions start a safe bounded path, the shield reverts to the original policy \( \pi \) (still satisfying bounded safety, by the second operand of 2).

In the worst case this requires enumerating all bounded paths in \( \varrho(s) \) before finding a safe one, and if \( n \) actions are available from each state there will be up to \( n^H \) such bounded paths, which can make shielding with large bounds \( H \) intractable. In practice, unsafe states are relatively rare and a safe path can be found quickly from most states. In particular, \( \pi \) itself will often be bounded safe for most states, and can be followed directly.

By guessing \( \pi \) is safe and rolling back to explore other paths only if a violation occurs, our algorithm has minimal computational overhead as long as \( \pi \) continues being safe. By also remembering

Figure 9: Additional Safety gained by applying a BPS with bound 5 to DQN. The other 26 properties were safe in 0% of traces with and without shielding and are not shown due to space limitations.
unsafe paths between time-steps, the shield can become performant even when encountering violations, for small bounds $H$, as evaluated in Figure 11.

**Experimental Results.** We evaluated the effectiveness of BPS on robustifying DQN and IQN against the safety properties including *Shallow* and *Minimal* properties. Recall that shallow properties are those that the we expect to need a prescience bound with 10 frames or fewer, and minimal properties are those that are necessary for scoring 10% of human game-play level.

Fig. 9 and Fig. 10 illustrate the performance of the DQN- and IQN-trained agents before and after applying BPS. The prescience bound of the shield in both experiments is $H = 5$. We initialised each game:property with $v = 30$ rounds of no-ops and monitored safety violations over all 30 generated traces. Note that applying BPS significantly improved the performance of both algorithms in Shallow properties, and with no further training both DQN and IQN fully satisfied the safety properties. This comes at a minimal computation cost as compared to re-training DRL algorithms to achieve the same performance.

However, we emphasise that the relative computational cost of BPS is exponential with respect to its prescience bound Fig. 11. This becomes a pressing issue when applying BPS to games and properties that require a much larger prescience bound. An example of such a game and property is *Bowling:no-hit* where the agent needs to have a prescience bound of hundreds of frames to avoid property violation (Fig. 3).

6 CONCLUSION

This paper proposed BPS, the first explicit-state bounded prescience shield for DRL agents in Atari games. We have defined a library of 43 safety specifications that characterise "safe behaviour". Despite the fact that there is positive correlation between the reward and satisfaction of these properties, we found that all of the top-performing DRL algorithms violate these safety properties across all the games we have considered. In order to analyse these failures we have applied explicit-state model checking to explore all possible traces induced by a trained agent. An analysis of these results suggests that most agents satisfy most of the safety properties most of the time, but that (relatively) rare violations remain. We conjecture that this finding is due to the fact that the policy of these agents is driven by an expected reward, which may be an ill-fit when the goal is to obtain a worst-case guarantee. Based on this observation we propose a countermeasure that applies our explicit-state exploration to implement bounded safety check we call bounded prescience shield to mitigate the unsafe behaviour of DRL agents. We demonstrate that our shield improves the overall safety of all agents across all games at minimal computational cost, delivering the agents that are, to the best of our knowledge, the safest agents available for ALE games. We observe that our safe agents obtain only marginally higher rewards on average, which offers an explanation why DRL training does not prevent the safety violations.

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