

# COMBATING DEEP REINFORCEMENT LEARNING'S SISYPHEAN CURSE WITH INTRINSIC FEAR

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## ABSTRACT

To use deep reinforcement learning in the wild, we might hope for an agent that can avoid catastrophic mistakes. Unfortunately, even in simple environments, the popular deep Q-network (DQN) algorithm is doomed by a Sisyphian curse. Owing to the use of function approximation, these agents eventually forget experiences as they become exceedingly unlikely under a new policy. Consequently, for as long as they continue to train, DQNs may periodically relive catastrophic mistakes. In this paper, we demonstrate unacceptable performance of DQNs on two toy problems. We then introduce *intrinsic fear*, a new method that mitigates these problems by avoiding states deemed dangerous. Our approach incorporates a second model trained via supervised learning to predict the probability of catastrophe within a short number of steps. This score then acts to penalize the Q-learning objective, shaping the reward function away from catastrophic states.

## 1 INTRODUCTION

Following success on Atari games (Mnih et al., 2015) and the board game Go (Silver et al., 2016), many researchers have begun exploring practical applications of deep reinforcement learning (DRL). With DRL, we might hope to replace simple hand-coded control policies with continuously learning agents. Some investigated applications include robotics (Levine, 2016), dialogue systems (Fatemi et al., 2016; Lipton et al., 2016), energy management (Night, 2016), and self-driving cars (Shalev-Shwartz et al., 2016). Amid this push to apply DRL, we might ask, *can we trust these agents in the wild?*

Agents acting in real world environments might possess the ability to cause catastrophic outcomes. Consider a self-driving car that might hit pedestrians, or a domestic robot that might injure a child. We might hope to prevent DRL agents from ever making catastrophic mistakes. But doing so requires extensive prior knowledge of the environment in order to constrain the exploration of policy space (Garcia & Fernández, 2015). Such knowledge may not always exist. In this paper, we don't assume prior knowledge of the state-space.

Already, we should note that multiple, conflicting definitions of safety and catastrophe exist, a problem that invites further philosophical consideration. We will return to this matter in Section 3. For now, we introduce a specific but plausible notion of a catastrophe. Suppose that catastrophes are a subset of states that are terminal, yielding a return of 0 and that returns are greater than or equal to 0 for non-catastrophic states. Moreover, we assume that a policy can perform sufficiently well without even coming near a catastrophe state. Note that this may not hold for general RL problems. In a cliff world, the pot of gold might lie on the ledge of a cliff. But for a self-driving car, we don't suspect that it ever should have to come within a split-second decision of committing murder. Finally,

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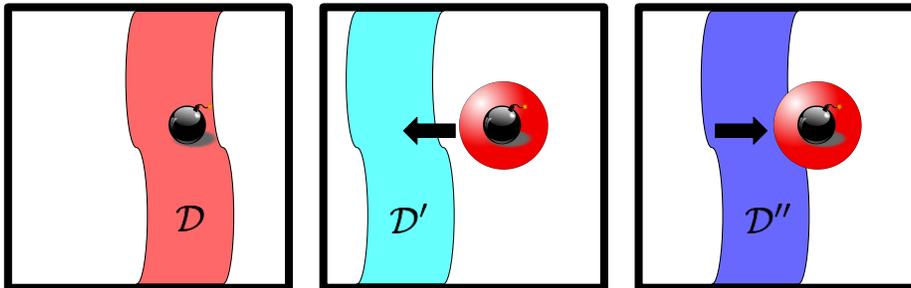


Figure 1: With typical deep reinforcement learning techniques, an agent may forget about catastrophic failure modes as they become unlikely under an updated policy. With *intrinsic fear*, we learn to recognize danger zones (red circles) around catastrophes and shape reward functions away from these zones.

while we don't assume prior knowledge of which states are dangerous, we do assume the existence of catastrophe detector. After encountering a catastrophic state, an agent can realize this and take action to avoid dangerous states in the future.

Given this definition, we address two challenges: First, can we expect DRL agents, after experiencing some number of catastrophic failures, to avoid perpetually making the same mistakes? Second, can a DRL agent learn to avoid catastrophes after only a small number of catastrophic experiences? Our experiments show that even on toy problems, the deep Q-network (DQNs), a basic algorithm behind many of today's state of the art DRL systems, struggles on both counts. Even in toy environments, DQNs may encounter thousands of catastrophes before avoiding them and may periodically repeat old errors so long as they continue to learn. We call this latter problem the Sisyphian curse.

This poses a formidable obstacle to using DQNs in the real world. How can we hand over responsibility for any consequential actions (control of a car, say) to a DRL agent if it may be doomed to periodically remake every kind of mistake, however grave, so long as it continues to learn? Imagine a self-driving car that had to periodically hit a few pedestrians in order to remember that it's undesirable.

Note that traditional tabular agents do not suffer from the Sisyphian curse. In the tabular setting, an RL agent never forgets the learned dynamics of its environment, even as its policy evolves. Thus, if the Markovian assumption holds, eventual convergence to a globally optimal policy is guaranteed. Unfortunately, the tabular approach becomes infeasible as state spaces grow large.

The trouble owes to the use of function approximation (Murata & Ozawa, 2005). When training a DQN, we successively update a neural network based on experiences. These experiences might be sampled in an online fashion, from a trailing window (*experience replay buffer*), or uniformly from all past experiences. Regardless of which mode we use to train the network, eventually, states that a learned policy never encounters will come to form an infinitesimally small region of the training distribution. At such time, our networks are subject to the classic problem of catastrophic interference McCloskey & Cohen; McClelland et al. (1995). Nothing prevents the DQN's policy from drifting back towards one that revisits catastrophic, but long-forgotten mistakes.

More formally, we could characterize the source of failure as:

- Training under distribution  $\mathcal{D}$ , our agent produces a safe policy  $\pi_s$  that avoids catastrophes
- Collecting data generated under  $\pi_s$  yields a distribution  $\mathcal{D}'$
- Training under  $\mathcal{D}'$ , the agent produces  $\pi_d$ , a policy that once again experiences catastrophes

In this paper, we illustrate the brittleness of modern deep reinforcement learning algorithms. We introduce a simple pathological problem called *Adventure Seeker*. This problem consists of a one-dimensional continuous state, two actions, simple dynamics and a clear analytic solution. Nevertheless, the DQN fails. We then show that similar dynamics exist in the classic RL environment Cart-Pole.

To combat these problems, we propose *intrinsic fear* (Figure 1). In this heuristic approach, alongside the DQN, we train a supervised *danger model*. The danger model predicts which states are likely to lead to a catastrophe within some number of steps  $k_r$ . The output of this model (a probability) is then scaled by a *fear factor* and used to penalize the Q-learning target. Our approach bears some resemblance to intrinsic motivation Chentanez et al. (2004). But instead of perturbing the reward function to encourage the discovery of novel states, we perturb it to discourage the rediscovery of catastrophic states.

## 2 BACKGROUND: DEEP Q-LEARNING

For context we briefly review deep Q-learning. Over a series of turns, an agent interacts with its environment via a Markov decision process, or MDP,  $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \gamma)$ . At each step  $t$ , an agent observes a state  $s \in \mathcal{S}$ . The agent then chooses an action  $a \in \mathcal{A}$  according to some policy  $\pi$ . In turn, the environment transitions to a new state  $s_{t+1} \in \mathcal{S}$  according to transition dynamics  $\mathcal{T}(s_{t+1}|s_t, a_t)$  and generates a reward  $r_t$  with expectation  $\mathcal{R}(s, a)$ . This cycle continues until each episode terminates.

The goal of an agent is to maximize the cumulative discounted return  $\sum_{t=0}^T \gamma^t r_t$ . Temporal-differences (TD) methods (Sutton, 1988) such as Q-learning (Watkins & Dayan, 1992) model the Q-function, which gives the *optimal* discounted total reward of a state-action pair; the greedy policy w.r.t. the Q-function is optimal (Sutton & Barto, 1998). Most problems of practical interests have large state spaces, thus the Q-function has to be approximated by parametric models such as neural networks.

In deep Q-learning, this is typically accomplished by alternately collecting experiences by acting greedily with respect to  $Q(s, a; \theta_Q)$  and updating the parameters  $\theta_Q$ . Updates proceed as follows. For a given experiences  $(s_t, a_t, r_t, s_{t+1})$ , we minimize the squared Bellman error:

$$\mathcal{L} = (Q(s_t, a_t; \theta_Q) - y_t)^2 \quad (1)$$

for  $y_t = r_t + \gamma \cdot \max_{a'} Q(s_{t+1}, a'; \theta_Q)$ . Traditionally, the parameterised  $Q(s, a; \theta)$  is trained by stochastic approximation, estimating the loss on each experience as it is encountered, yielding the update:

$$\theta_{t+1} \leftarrow \theta_t + \alpha(y_t - Q(s_t, a_t; \theta_t)) \nabla Q(s_t, a_t; \theta_t). \quad (2)$$

Q-learning methods also require an exploration strategy, and for simplicity we consider only the  $\epsilon$ -greedy heuristic. However, our techniques apply equally for Thompson-sampling based exploration. For a thorough overview of RL fundamentals, we refer the reader to Sutton & Barto (1998).

A few tricks are often useful to stabilize Q-learning with function approximation. Of particular relevance to this work is experience replay (Lin, 1992): the RL agent maintains a buffer of past experiences, applying TD-learning on randomly selected mini-batches of experience to update the Q-function. This technique has proven effective to make Q-learning more stable and more data-efficient (Lin, 1992; Mnih et al., 2015).

## 3 SAFE REINFORCEMENT LEARNING

At the outset we ought to consider a more formal treatment of safe reinforcement learning. Precisely what do we mean by *safety*, *catastrophe*, or *danger*? The literature offers several notions of safety in reinforcement learning. Garcia & Fernández (2015) provide a comprehensive review of this literature, suggesting that existing approaches can be divided into two categories.

The first approach consists of modifying the objective function. Traditionally, in a Markov decision process, a reinforcement learner seeks to maximize expected return. Hans et al. (2008) defines a *fatality* as a return below some threshold  $\tau$ . In this view, an agent might seek to minimize the worst case scenario instead of maximizing the expected return. Along these lines, Heger suggested the  $\hat{Q}$ -learning objective:

$$\hat{Q} = \min(\hat{Q}(s_t, a_t), r_{t+1} + \gamma \max_{a_{t+1} \in \mathcal{A}} \hat{Q}(s_{t+1}, a_{t+1}))$$

Other relevant papers suggest modifying the objective to address risk. While classic Q-learning objective addresses only expected returns, alternative objectives penalize policies for returns with high-variance Garcia & Fernández (2015). Other suggest incorporating external knowledge into the exploration process. In the extreme case, we might confine our policy search to the subset of policies known to be *safe*.

We see the following problem. The first category of methods acts only on the summary statistics of the return. This can be beneficial because it requires no foreknowledge. But the drawback is that they fundamentally change the objective everywhere, even in states that we might not be worried about. On the other hand, processes relying on expert knowledge may presume an unreasonable level of foreknowledge.

In this paper, we propose a new formulation of the safety problem. We suppose there exists a subset  $\mathcal{C} \subset \mathcal{S}$  of catastrophic states. These states have minimum return, and thus resemble the fatalities of Hans et al. (2008). Additionally we assume that it’s reasonable for policy to avoid even getting close to these states.

In other words, there exist good policies that never get within a few hops of a catastrophe state. Just as a child shouldn’t run with scissors, a self-driving car should never be one split-second decision away from killing a passenger or pedestrian. Note, this imposes some prior knowledge. In a general, unknown environment, it might be that a good policy should get very close to a fatality in order to maximize reward.

We don’t assume advanced knowledge of  $\mathcal{C}$ , but we do assume the agent possesses a *catastrophe detector*. In the case of a self-driving car, this might be an impact detector. Even if we can’t anticipate all the situations which might lead to an accident, we can recognize one when it has already happened and take measures to avoid danger zones around these states in the future.

The notion of danger zone suggests some measure of proximity. Informally, we conceive of *danger* as the likelihood of entering a catastrophe state  $c \in \mathcal{C}$  within a short number of steps. Note, this probability depends on the policy. In this paper, we collect the experiences used to train the danger model from the entire training period. So the likelihood here is determined based on the observations of many policies over the course of training. Explicitly modeling danger zones can be useful for two reasons. First, it provides a mechanism to avoid oscillating policy learners from repeatedly encountering catastrophe states. Second, reward-shaping to avoid danger zones can significantly reduce the sample complexity of exploration.

## 4 TWO PATHOLOGICAL FAILURE CASES

We now present two pathological environments. In the *Adventure Seeker* (Figure 2a) environment, we imagine a player placed on a hill, sloping upward to the right. At each turn, the player can move to the right (up the hill) or left (down the hill). The environment adjusts the player’s position accordingly, adding some random noise. Between the left and right edges of the hill, the player gets more reward for spending time higher on the hill. But if the player goes too far to the right, she will fall off (a *catastrophic state*), terminating the episode and receiving a return of 0.

Formally, the state consists of a single continuous variable  $s \in [0, 1.0]$ , denoting the player’s position. The starting position for each episode is chosen uniformly at random in the interval  $[.25, .75]$ . The available actions consist only of  $\{-1, +1\}$  (*left* and *right*). Given an action  $a_t$  in state  $s_t$ ,  $\mathcal{T}(s_{t+1}|s_t, a_t)$  gives successor state  $s_{t+1} \leftarrow s_t + .01 \cdot a_t + \eta$  where  $\eta \sim \mathcal{N}(0, .01^2)$ . At each turn, the player gets reward equal to  $s_t$  (proportional to height). The player falls off the hill, entering the catastrophic terminating state, whenever an action would result in successor state  $s_{t+1} > 1.0$  or  $s_{t+1} < 0.0$ .

This game admits an obvious analytic solution. There exists some threshold above which the agent should always choose to go left, and below which it should always go right. Even an infant could grasp the gist of this solution. And yet a state-of-the-art DQN model learning online or with experience replay successively plunges to its death. To be clear, the DQN does learn a near-optimal thresholding policy quickly. But over the course of continued training, the agent oscillates between a reasonable thresholding policy and one which always moves right, regardless of the state. The pace of this oscillation evens out and all networks (over multiple runs) quickly reach a constant catastrophe per

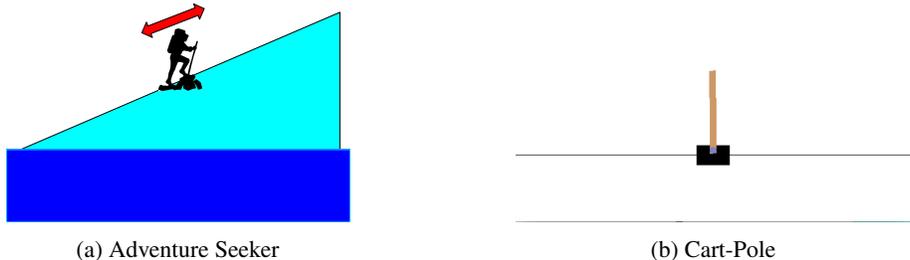


Figure 2: Two simple pathological environments

turn rate (Figure 3a) that does not attenuate with continued training. How could we ever trust a system that can't solve *Adventure Seeker* to make consequential real-world decisions?

Cart-Pole (Figure 2b) is a classic RL environment in which an agent tries to balance a pole atop a cart. Qualitatively, the game exhibits four distinct catastrophe modes. The pole could fall down to the right or fall down to the left. Additionally, the cart could run off the right boundary of the screen or run off the left.

Formally, at each time, the agent observes a four-dimensional state vector  $(x, v, \theta, \omega)$  consisting respectively of the cart position, cart velocity, pole angle, and the pole's angular velocity. At each time step, the agent chooses an action, applying a force of either  $-1$  or  $+1$ . For every time step that the pole remains upright and the cart remains on the screen, the agent receives a reward of 1. If the pole falls, the episode terminates, giving a return of 0 from the penultimate state. In experiments, we use the implementation *CartPole-v0* contained in the openAI gym Brockman et al. (2016). Like *Adventure Seeker*, this problem admits an analytic solution. A perfect policy should never drop the pole. But, as with *Adventure Seeker*, a DQN converges to a constant rate of catastrophes per turn.

## 5 INTRINSIC FEAR

We now introduce intrinsic fear (Algorithm 1), a novel mechanism for avoiding catastrophes when learning online with function approximation. In our approach, we maintain both a DQN and a separate, supervised *danger model*. Our *danger model* provides an auxiliary source of reward, penalizing the Q-learner for entering dangerous states.

The goal in learning this smooth danger zone is twofold. First the knowledge that regions around certain states should be avoided represents a source of prior knowledge that can accelerate learning in some environments. Second, by using danger zones to shape rewards away from catastrophic states, we allow oscillating policies to drift close (but not too close) to catastrophe states, giving them opportunity to adjust trajectories away, without having to re-experience the catastrophe. We draw some inspiration from the idea of a parent scolding a child for running around with a knife. The child can learn to adjust its behavior without actually having to stab someone.

We make the following conservative assumption. While we don't know anything in advance about the state space, we possess a *catastrophe detector* which can identify each catastrophe as it happens. We also assume that the agent collects a buffer of previously observed states. After it detects each catastrophe, the agent can refer back to the trajectory that led up to it.

The technique works as follows: In addition to the DQN, we maintain a binary classifier that we term a *danger model*. In our case, it is a neural network of the same architecture as the DQN (but for the output layer). In general, it could be any supervised model. The danger model's purpose is to identify the likelihood that any state will lead to catastrophe within  $k$  moves. In the course of training, our agent adds each experience  $(s, a, r, s')$  to the experience replay buffer. As each catastrophe is reached at the  $n_{th}$  turn of an episode, we add the  $k_r$  (*fear radius*) states leading up to the catastrophe to a list of *danger states*. We add the preceding  $n - k_r$  states to a list of *safe states*. When  $n < k_r$ , all states for that episode are added to the list of danger states.

**Algorithm 1:** Training DQN with Intrinsic Fear

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1 function Train(  $Q(\cdot, \cdot; \cdot)$ ,  $d(\cdot; \cdot)$ ,  $T$ ,  $\lambda$ ,  $k_\lambda$ ,  $k_r$ );
2 Input : Two model architectures:  $Q$  (a DQN) and  $d$  (the danger model), time limit  $T$ , fear factor  $\lambda$ ,
   fear phase-in length  $k_\lambda$ , fear radius  $k_r$ 
3 Output : Learned parameters  $\theta_Q$  and  $\theta_d$ 
4 Initialize parameters  $\theta_Q$  and  $\theta_d$  randomly
5 Initialize replay memory  $\mathcal{D}_e$ , danger states  $\mathcal{D}_d$ , and safe states  $\mathcal{D}_s$ 
6 for  $t$  in  $1:T$  do
7   With probability  $\epsilon$  select random action  $a_t$ 
8   Otherwise, select action  $a_t = \max_{a'} Q(s_t, a'; \theta_Q)$ 
9   Execute action  $a_t$  in environment, observing reward  $r_t$  and successor state  $s_{t+1}$ 
10  Store transition  $(s_t, a_t, r_t, s_{t+1})$  in  $\mathcal{D}$ 
11  if  $s_{t+1}$  is a terminal state then
12    Add states  $s_{t-k_r}$  through  $s_t$  to  $\mathcal{D}_d$ 
13    Add states  $s_{t-n_e}$  through  $s_{t-k_r-1}$  to  $\mathcal{D}_s$ 
14  end
15  Sample random minibatch of transitions  $(s_\tau, a_\tau, r_\tau, s_{\tau+1})$  from  $\mathcal{D}$ 
16  Set  $\lambda_t \leftarrow \min(\lambda, \frac{\lambda \cdot t}{k_\lambda})$ 
17  Set  $y_t \leftarrow \begin{cases} r_t - \lambda_t, & \text{for terminal } s_{\tau+1} \\ r_t + \max_{a'} Q(s_{t+1}, a'; \theta_Q) - \lambda \cdot d(s_{t+1}; \theta_d) & \text{for non-terminal } s_{t+1} \end{cases}$ 
18  Apply SGD step  $\theta_Q \leftarrow \theta_Q - \eta \cdot \nabla_{\theta_Q} (y_\tau - Q(s_\tau, a_\tau; \theta_Q))^2$ 
19  Sample random mini-batch  $s_j$  with 50% of examples from  $\mathcal{D}_d$  and 50% from  $\mathcal{D}_s$ 
20  Set  $y_j \leftarrow \begin{cases} 1, & \text{for } s_j \in \mathcal{D}_d \\ 0, & \text{for } s_j \in \mathcal{D}_s \end{cases}$ 
21  Apply SGD step  $\theta_d \leftarrow \theta_d - \eta \cdot \nabla_{\theta_d} \text{loss}_d(y_j, d(s_j; \theta_d))$ 
22 end

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Then after each turn, in addition to making one update to the Q-network, we make one mini-batch update to the danger model. To make this update, we sample 50% of states from the *danger states*, assigning them label 1 and 50% of states from the *safe states*, assigning them label 0.

For each update to the DQN, we perturb the TD target  $y_t$ . Instead of updating  $Q(s_t, a_t; \theta_Q)$  towards  $r_t + \max_{a'} Q(s_{t+1}, a'; \theta_Q)$ , we introduce the *intrinsic fear* to the model via the target:

$$y_t^{IF} = r_t + \max_{a'} Q(s_{t+1}, a'; \theta_Q) - \lambda \cdot d(s_{t+1}; \theta_d)$$

where  $d(s; \theta_d)$  is the danger model and  $\lambda$  is a *fear factor* determining the scale of the impact of intrinsic fear on the Q update.

Over the course of our experiments, we discovered the following pattern. To be effective, the *fear radius*  $k_r$  should be large enough that the model can detect danger states at a safe distance where they can still be avoided. When the fear radius is too small, the danger probability is only nonzero at a points from which catastrophes are inevitable and intrinsic fear doesn't help. On the other hand, when the *fear radius* is too large, all states are predicted to be danger states. For example, early in training, all Cart-Pole experiences are shorter than 20 experiences. So a *fear radius* of 20 leads our models model to diverge. To overcome this problem, we gradually phase in the *fear factor* from 0 to  $\lambda$  reaching full strength at predetermined time step  $k_\lambda$ . In our Cart-Pole experiments we phase in over  $1M$  steps.

## 6 EXPERIMENTS

To assess the effectiveness of the intrinsic fear model, we evaluate both a standard DQN (DQN-NoFear) and one enhanced by *intrinsic fear* (DQN-Fear). In both cases, we use multilayer perceptrons (MLPs) with a single hidden layer and 128 hidden nodes. We train all MLPs by stochastic gradient descent using the Adam optimizer Kingma & Ba (2015) to adaptively tune the learning rate.

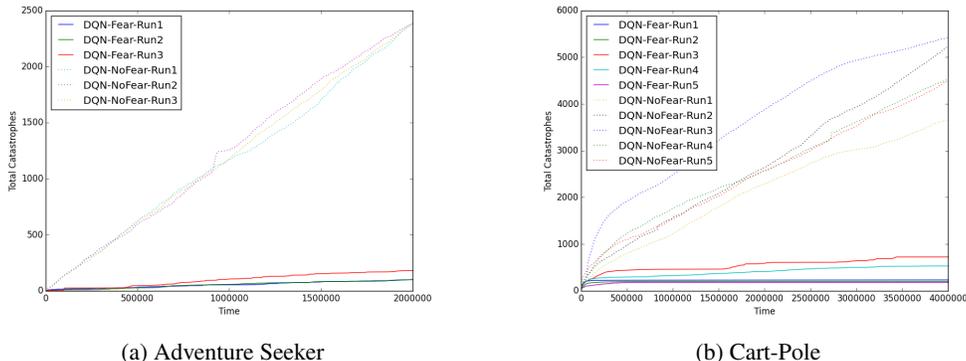


Figure 3: Total catastrophes for DQNs and *Intrinsic Fear* DQNs on Adventure Seeker and Cart-Pole. We don't plot per-episode return for these games because (i) the best models quickly become so good that they never terminate (ii) avg return is the inverse of catastrophe rate for cart-pole.

Because, for the *Adventure Seeker* problem, an agent can escape from danger with only a few time steps of notice, we set the fear radius  $k_r$  to 5. We phase in the fear factor quickly, reaching full strength in just 1000 moves. On this problem we set the fear factor  $\lambda$  to 40.

For *Cart-Pole*, we set a wider fear radius of  $k_r = 20$ . We initially tried training this model with a shorter fear radius but made the following observation. Some models would learn well surviving for millions of experiences, with just a few hundred catastrophes. This compared to a DQN (Figure 3) which would typically suffer 4000-5000 catastrophes. When examining the output from the danger models on successful vs unsuccessful runs, we noticed that the unsuccessful models would output danger of probability greater than .5 for precisely the 5 moves before a catastrophe. But by that time it would be too late for an agent to correct course. In contrast, on the more successful runs, the danger model would often output predictions in the range .1 – .5. We suspect that this gradation between mildly dangerous states and those where danger is imminent provided a richer reward signal to the DQN. Accordingly, we lengthened the fear radius to 20 so that some states might be ambiguous (could show up in either *danger list*  $\mathcal{D}_a$  or *safe list*  $\mathcal{D}_s$ ).

On both the Adventure Seeker and Cart-Pole environments, the DQNs augmented by intrinsic fear far outperform their otherwise identical counterparts (Figure 3). We compared this approach against some traditional approaches, like memory based methods for preferentially sampling failure cases but they could not improve over the DQN.

## 7 RELATED WORK

The paper addresses safety in RL, intrinsically motivated RL, and the stability of Q-learning with function approximation under distributional shift. Our work also has some connection reward shaping. While space constraints preclude adequate treatment of all prior work, we attempt to highlight the most relevant papers here.

**The Stability of RL with Function Approximation:** The potential oscillatory or divergent behavior of Q-learners with function approximation has been previously identified (Boyan & Moore, 1995; Baird et al., 1995; Gordon, 1996). But these papers address neither AI safety nor RL. Murata & Ozawa (2005) addresses the problem of catastrophic forgetting owing to distributional shift in RL with function approximation, proposing a memory-based solution. Outside of reinforcement learning, a number of papers address problems related to non-stationary data, including a book on covariate shift (Sugiyama & Kawanabe, 2012).

**Safety in Reinforcement Learning:** Several papers address safety in RL. Garcia & Fernández (2015) provide a thorough review on the topic, dividing the existing works into those which perturb the objective function and those which use external knowledge to improve the safety of exploration. Hans et al. (2008) defines a fatal state as one from which one receives a return below some safety threshold  $\tau$ . They propose a solution comprised of two components. One, the *safety function*,

identifies unsafe states. The other, denoted the *backup model*, is responsible for navigating away from the critical state. Their work does not address function approximation, instead focusing on a domain where a tabular approach is viable. Moldovan & Abbeel (2012) gives a definition of safety based on ergodicity. They consider a fatality to be a state from which one cannot return to the start state. Shalev-Shwartz et al. (2016) provides theoretical analysis considering how strong a penalty should be to discourage accidents. They also consider hard constraints to ensure safety, an approach that differs from ours. None of the above works address the case where distributional shift dooms an agent to perpetually revisit catastrophic failure modes.

**Intrinsically Motivated Reinforcement Learning:** A number of papers have investigated the idea of intrinsically motivated reinforcement learners. Intrinsic motivation refers to an intrinsically assigned reward, in contrast to the extrinsic reward that comes from the environment. Typically intrinsic motivation is proposed as a way to encourage exploration of an environment (Schmidhuber, 1991; Bellemare et al., 2016) and to acquire a modular set of skills Chentanez et al. (2004); Barto et al.. In principle, such motivation can lead agents to explore intelligently even when extrinsic rewards are sparse. Some papers refer to the intrinsic reward for discovery as *curiosity*. Like classic work on intrinsic motivation, our methods operate by perturbing the reward function. But instead of assigning bonuses to encourage discovery of novel transitions, we assign penalties to discourage re-discovery of catastrophic transitions.

## 8 DISCUSSION

Our experiments suggest that DQNs may be too brittle for use in real-world applications where harm can come of actions. While at present we show results only on toy models, we expect that similar dynamics are embedded in more complex domains. Consider a domestic robot acting as a barber. The robot might receive positive feedback for giving a closer shave. This reward encourages closer contact at a steeper angle. Of course, the shape of this reward function belies the catastrophe lurking just past the optimal shave. Similar dynamics might be found in a vehicle which is rewarded for traveling faster but could risk an accident with excessive speed.

These scenarios are not so unlike the pathological case presented in Adventure Seeker. We might even say these shortcomings seem analogous to the fundamental inability of linear models to solve XOR. But while XOR can be solved by simply incorporating hidden layers of representation, it's less obvious how to overcome these pitfalls.

These early successes of the intrinsic fear model suggests that for some classes of problems we might avoid perpetual catastrophe and still enjoy the benefits of function approximation. In this work we assume the ability to recognize a catastrophe once it has happened. But we don't assume anything in advance about the precise form that the danger states might take in the state space. Our approaches seem appropriate for problems with some notion of proximity. A self-driving car can't run over a passenger in the next second if no people are in close proximity. But our methods might not be appropriate for other problems. For example, in a problem where a single action, from any state, can produce a catastrophe with high probability, our methods might fail.

This work represents a first step towards combating AI safety issues stemming from the use of function approximation in deep reinforcement learning. In follow-up work, we hope to formalize the notion of danger presented here. We hope to critically examine competing definitions of catastrophe and of danger, to organize them into a taxonomy and to develop theory addressing the most promising ones. We also hope to explore the effectiveness of our technique on more complex domains. In precisely what sorts of environments should our approach work? Under what conditions can we expect it to fail?

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