Reinforcement Learning Generalization with Surprise Minimization

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Abstract

Generalization remains a challenging problem for reinforcement learning algorithms, which are often trained and tested on the same set of environments. When test environments are perturbed but the task is semantically the same, agents can still fail to perform accurately. Particularly when they are trained on high-dimensional state spaces, such as images. We evaluate an surprise minimizing agent on a generalization benchmark to show an additional reward learned from a density model can help agents acquire robust skills on unseen procedurally generated diverse environments.

1 Introduction

Reinforcement learning (RL) with neural networks has been successfully applied to many scenarios. Most notably, it has beaten human players in board games [1, 2] and reached expert level in video games [3, 4]. It has also improved complex robotic control tasks [5]. However, deep RL agents still struggle to generalize to new environments, even when the nature of the task remain similar [6, 7, 8]. Agents can overfit to the training levels in a video game with near-optimal policy but fail to perform at unseen levels [9]. This problem makes RL agent unreliable for real world applications where robustness and generalized behaviours are important [10, 11].

Recent work (SMiRL) [12] inspired by the free energy principle [13] has shown that emergent behaviours can arise from minimizing expected future surprises in order to maintain homeostasis. Probability distribution over the observation space is predicted by decoding a state representation density model learned from history, such as using a simple normally distributed model or a richer variational autoencoder [14]. More importantly, adding a surprise minimizing reward to the raw episodic task reward has shown faster reward acquisition. It may potentially help the agent achieve better generalization since it is integral that surprise minimization learns robust policies in order to perform well in a dynamically changing environment.

To evaluate generalization performance with separate and diverse training and test levels, we use the Procgen benchmark [15]. It consists of 16 game-like environments designed using procedural content generation [16]. Compared to human-generated level progression for each game, procedural generation creates highly randomized content that is suitable for evaluating generalization. This promotes the agents to learn a policy that is robust against changes in variables such as level layout and initial location of entities. In the paper, the authors trained agents using Proximal Policy Optimization (PPO) [17] for 200M time-steps under the hard difficulty setting. The agents are trained on a finite set of levels and tested on the full distribution of levels to evaluate generalization.

We show that adding surprise minimizing information through rewards learned by the density model on states of the training history can improve generalization on game levels that are different than what the agent was trained on. Since the history consists of episodes in levels that are dynamic and
unpredictable, the agent must minimize the expected future surprise according to the density model in order to learn robust behaviours to generalize to the changing nature of its environments.

2 Related Work

Several RL benchmarks dealing with generalization have emerged in recent years. Particularly, procedural generation is used to create diverse game environments [18, 19]. Obstacle Tower [20] is a 3D, third person, procedurally generated environment. The agent is required to learn both low-level control and high-level planning problems. The Sonic benchmark [21] is based on the Sonic the Hedgehog video game franchise. However, generalization performance was poor as the benchmark was targeted at few-shot learning. They evaluated the baselines using algorithms such as PPO [17] and Rainbow [22]. Safety Gym [23] consists of a suite of 18 high-dimensional continuous control environments for safe exploration under the constrained MDP framework. While their environments do have a high level of randomization, their main objective is to enforce safety and to minimize the constraint cost.

Various techniques have been proposed to achieve better generalization for RL agents. One involves adding a convolutional layer in between the input image and the neural network policy [24]. This layer is randomly initialized at every iteration to create a variety of randomized training data. It has been shown [25] that robust representations can be learned by the RL agent if diverse observations are provided during training. However, such domain randomization approaches often suffer from high sample complexity and high variance in the policy performance. Zhang et al. report insightful discussions on the nature of RL over-fitting [7]. They experiment on procedurally generated grid-world mazes and find that agents have a tendency to memorize specific levels in a given training set. Sticky actions [26] and random starts [27] fail to mitigate the generalization gap. Experiments on the CoinRun game [9] investigates the impact of supervised learning regularization techniques including L2 regularization, dropout, data augmentation, and batch normalization, which all helped narrow the generalization gap. Similar to [7], they also found that injecting stochasticity in environments with $\epsilon$-greedy action selection and increasing entropy bonus in PPO can both improve generalization. Stochasticity helped generalization to a greater extent than regularization techniques from supervised learning. Rather than altering the action selection procedure, we inject stochasticity through a different channel in the reward by learning state distributions from highly stochastic and dynamic environments from the Procgen benchmark.

3 Method

In the Procgen paper [15], agents are trained using PPO for 200M time-steps under the hard difficulty setting. Training requires approximately 24 GPU-hours per environment. We used OpenAI baselines [28] implementation of PPO, which has an IMPALA [29] network as the policy. Due to time and compute power constraints, we produce baselines using the easy difficulty setting. As recommended in the Procgen paper, we use training sets of 200 levels and trained for 25M time-steps.

We implement surprise minimizing rewards $r_{SM}$ based on a representation density model $p_{\theta_t}(s)$ as shown in Algorithm 1. This is an estimate of the distribution of visited states. This model is used to construct a surprise minimizing reward. In the surprise minimization framework, the optimal policy does not simply visit states that have high $p_{\theta_t}(s)$ now, but also those states that will change $p_{\theta_t}(s)$ such that it provides high likelihood to the states that it sees in the future.

We first model $p_{\theta_t}(s)$ using independent Gaussian distributions for each dimension in our observations. A buffer is created for storing recent batches in the history during training. The size of the buffer is 20 times the mini-batch size. Each batch has of 16384 RGB visual observations with dimensions of $64 \times 64 \times 3$. The observations may consist of multiple episodes depending on the agent’s performance. We transform and normalize all RGB observations to $64 \times 64$ gray-scale images before they are stored in the buffer. Before each mini-batch update to our policy, a surprise minimizing reward is computed from the buffer. For a single state $s$ in the buffer, the SM reward is computed as:

$$r_{SM} = - \sum_i \left( \log \sigma_i + \frac{(s_i - \mu_i)^2}{2\sigma_i^2} \right)$$
where $\mu_i$ and $\sigma_i$ are the sample mean and standard deviation calculated from the data buffer and $s_i$ is the $i^{th}$ observation feature of $s$. This reward is computed for each batch, rather than for each episode in SMiRL [12]. Therefore, it is an instance of non-episodic surprise minimization. This is also the case for the VAE method mentioned below.

**Algorithm 1** PPO + Normal Algorithm

1: Initialize game environment $Env$
2: Initialize PPO with IMPALA policy parameters $\phi$
3: Initialize Data Buffer $D_0$
4: for batch $b_1, b_2, \cdots, b_T$ do
5: $D_t \leftarrow D_{t-1} \cup \{b_t\}$
6: $a_t \leftarrow \pi_\phi(a_t|b_t)$
7: $r_t \leftarrow Env(b_t)$
8: $\theta_t = \{\mu_t, \sigma_t\}$ computed from $D_t$ \> across each dimensions for each state in the $D_t$
9: $r^t_{SM} = \log p_{\theta_t}(b_t)$ \> Normal SM rewards
10: $\phi \leftarrow PPO(\phi, b_t, a_t, r_t + \alpha r^t_{SM})$

The SM reward will be added to the raw episodic reward for the specific task via the equation:

$$r_{combined}(s) = r_{task}(s) + \alpha r_{SM}(s)$$

$\alpha$ is a hyper-parameter selected to balance the magnitudes of the two rewards. Performance in the SM setting will be compared against the PPO baselines. Evaluation scores will be the mean reward across all episodes for each mini batch update achieved during training and testing. It will range from 0 to 10 for CoinRun and 0 to 12 for BossFight.

Additionally, as presented in Algorithm 2, we produce a variational autoencoder (VAE) instead of Normal density to learn a richer representation from observations in episodes. We trained the VAE with raw RGB observations without adjustment. Similar to [12], we train this VAE online across all episodes since it requires more data. Distinct from the VAE prior, a batch-specific distribution $p_{\theta_t}(z)$ is tracked to compute the SM reward. $p_{\theta_t}(z)$ is represented as a normal distribution with diagonal covariance. The parameters of this distribution are computed from the VAE encoder outputs of the each batch observations in batch $D_t$ of size $b$ at time $t$ (line 9 in Algorithm 2):

$$z_j = E[q(z_j|s_j)], s_j \in D_t, j = 1, \cdots, b$$

$$\mu = \frac{\sum_{j=0}^{b} z_j}{b+1}, \sigma = \frac{\sum_{j=0}^{b} (\mu - z_j)^2}{b+1}, \theta_t = \{\mu, \sigma\}$$

To compute the SM rewards for each observation, we take the log probability $\log p_{\theta_t}(z_j)$ of this normal distribution evaluated at each $z_j$ in the batch. Similarly, this reward will be aggregated with the task reward using the hyper-parameter $\alpha$ to produce training signals for the PPO policy.

**Algorithm 2** PPO + VAE Algorithm

1: Initialize game environment $Env$
2: Initialize PPO with IMPALA policy parameters $\phi$
3: Initialize VAE $\psi_0$
4: for batch $b_1, b_2, \cdots, b_T$ do
5: update $\psi_\phi$ given observations in $b_t$
6: $a_t \leftarrow \pi_\phi(a_t|b_t)$
7: $r_t \leftarrow Env(b_t)$
8: $z_t \leftarrow VAE_{\psi_\theta}(b_t)$ \> compute parameter of diagonal Gaussian from latent variables
9: $\theta_t = \{\mu_t, \sigma_t\} \leftarrow z_t$ \> VAE SM rewards
10: $r^t_{SM} = \log p_{\theta_t}(z_t)$
11: $\phi \leftarrow PPO(\phi, b_t, a_t, r_t + \alpha r^t_{SM})$


4 Experimental Results

4.1 Normal Distribution

We trained and evaluated the PPO baseline on the game CoinRun, which is an inaugural environment in the Procgen benchmark first developed in 2018 [9]. The entire background environment in CoinRun will move relative to the agent’s movement to have the agent centred in the image. Thus, we also run experiments on another game BossFight, which has a static observation space.

![Figure 1: CoinRun and BossFight](image)

As suggested in [15], both training and testing are done under the easy difficulty setting for 25M steps to achieve computational efficiency on a single GPU. Training is done on the first 200 levels and testing is evaluated on the full distribution of levels.

**CoinRun** The goal of CoinRun is to collect the coin at the far right of a platform, and the player spawns on the far left. The player must dodge enemies and chasms that lead to death. Procgen’s version of CoinRun does not paint velocity information directly into the observations, which makes the environment more difficult. Procedural generation controls the number of platform sections, their corresponding types, the location of crates, and the location and types of obstacles.

![Figure 2: CoinRun - Baseline PPO: Train (Blue) vs. Test (Orange) Score](image)

We first produce the PPO baseline and evaluate the results using the mean raw episodic return. Figure 2 confirms the finding from [15] that there is a gap between training and testing performances. However, the gap is much smaller considering the difficulty mode is set to easy and we trained on...
200 levels rather than 500 levels. A closer look shown in Figure 4 portrays the difference in mean rewards between the training and testing curves. The agent cannot achieve as good of a score on the test set after 1.5M steps.

We investigate the behaviour of the agent when it is trained on a combined reward of both the surprise minimizing reward and the raw return. We define the SM reward as a normally distributed state distribution from history as mentioned in Section 3. The hyper-parameter $\alpha$ of $10^{-4}$ is selected to downscale the SM reward to a similar level as the task reward. In Figure 7, we can see that scores achieved with the combined reward (PPO + Normal in orange) during 25M steps of training is lower than the baseline (PPO in blue) we produced. However, on the test set, the agent trained on both the task and SM rewards has comparable scores to training under the baseline with the task reward alone (see Figure 8). A comparison in Figure 3 shows that with the combined reward, the task rewards on the test set outperforms the training set at all steps. After 1.5M steps, the mean task reward is 7.78 for the training levels, and 9.37 for the testing levels. This suggests a simple Gaussian density model can provide additional information about the dynamics of the game, which helps the policy to generalize on test levels.

**BossFight** In this game, the agent controls a small star ship and must destroy a much bigger boss star ship, which randomly selects possible attacks to engage the agent. The agent must dodge the incoming projectiles to avoid its destruction. There are randomly scattered meteors for cover. The boss becomes vulnerable and its shields go down from time to time. At this point, the agent’s projectile attacks will damage the boss. The player receives a reward when the boss receives a certain amount of damage. The damage is accumulated until the boss is destroyed, where the player receives a large reward. Procedural generation controls certain game constants, including the boss health and the number of rounds in a level. It also selects the configuration of meteors in the level, and the attack pattern sequence the boss will follow.
We produced the same experiments on BossFight. This game is different to CoinRun as the visual background is more stable. In CoinRun, while the raw visual observations would shift according to how the agent moves, the only moving parts in BossFight are the boss, the agent and their lasers. An $\alpha$ of $10^{-6}$ works well to downscale SM reward. We found that there is a more prominent gap between train and test curves (Figure 5) in the PPO baseline. Furthermore, the learned policy is slow at attaining decent results on the test set, implying a worse generalization performance than CoinRun. By adding the Normal SM reward, we achieve better task rewards on the test set (Figure 6 in orange) and the gap between the two curves is reduced. Comparing the two test curves (Figure 10), the addition of a SM reward shows a higher task reward right from the beginning, indicating that it can help generalization performance.

4.2 Variational Autoencoder

The particular behaviour of a surprise minimizing agent is strongly influenced by the choice of state representation. We further implement a variational autoencoder [14, 30] during training to see if a more complex density model can better improve generalization than the simpler Gaussian case. The VAE has convolutional layers similar to [31], where they utilized it for autonomous driving environments. The autoencoder has a latent dimension of 100. We train this VAE online to produce latent representations over all the states in the observation batch $D_t$ to produce mean and variance of a multivariate normal distribution with the same dimension as the latent encoding. Every update to the VAE uses the same batch of observations as the policy update. We optimize the VAE and compute a prior for each batch to compute the surprise minimizing reward as described in Section 3. Note that due to computational constraints, we train the VAE along with our RL algorithm to 9.3 million steps for both games.

**CoinRun** We choose $\alpha$ to be $10^{-3}$ for CoinRun and observe that after 9M steps for training the policy and VAE, the task reward in Figure 7 (PPO + VAE in green) has already eclipsed the two
other methods. SM reward computed from the VAE helps the agent to achieve high task reward significantly faster than the baseline PPO. However, the test results using the policy trained for 9M steps does not achieve better generalization results in Figure 8. We think that the policy in combination with the additional reward from VAE may overfit to the training levels and thus the policy learned in combination with it cannot generalize to the unseen test levels.

**BossFight** For BossFight, we choose $\alpha$ to be $10^{-5}$ for balancing the two rewards. In the beginning of test (Figure 9), we see the same possible overfitting effect of the VAE approach, which results in lower test scores. But as testing progresses, the rewards get on par with the PPO + Normal method as shown in Figure 10.
Figure 10: BossFight Test Scores

5 Conclusion

In this project, we see the benefit of additional surprise minimizing reward on reinforcement learning generalization. Surprise minimization aims to predict states by learning a density model through history to minimize future surprises. The assumption underlying this framework is that the environment is constantly changing and the agent needs to maintain stability in order to achieve good performance and avoid surprises from the environment. This is a suitable framework for robustness since we would like the agent to be able to generalize in entropic environments with similar semantics. Additionally, by adding the surprise minimizing reward, stochasticity in the diverse Procgen environment is injected for training to improve generalization performance. There are aspects for improvements and further work. First, our analysis is limited to two games in the benchmark and further experiments should be run to determine the two methods’ effectiveness on all games, which may have different outcomes as we have discovered. The choice of the density model can also influence the generalization gap. To narrow the gap and prevent overfitting, careful tuning of the number of parameters or the structure might be needed for a rich model like the variational autoencoder. Further, the choice of the hyperparameter in determining the magnitude of surprise minimizing reward can make or break the training process and this brittleness can impact generalization performance on test levels.
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