The Dreaming Variational Autoencoder for Reinforcement Learning Environments

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Abstract. Reinforcement learning has shown great potential in generalizing over raw sensory data using only a single neural network for value optimization. There are several challenges in the current state-of-the-art reinforcement learning algorithms that prevent them from converging towards the global optima. It is likely that the solution to these problems lies in short- and long-term planning, exploration and memory management for reinforcement learning algorithms. Games are often used to benchmark reinforcement learning algorithms as they provide a flexible, reproducible, and easy to control environment. Regardless, few games feature a state-space where results in exploration, memory, and planning are easily perceived. This paper presents *The Dreaming Variational Autoencoder* (DVAE), a neural network based generative modeling architecture for exploration in environments with sparse feedback. We further present Deep Maze, a novel and flexible maze engine that challenges DVAE in partial and fully-observable state-spaces, long-horizon tasks, and deterministic and stochastic problems. We show initial findings and encourage further work in reinforcement learning driven by generative exploration.

Keywords: Deep Reinforcement Learning · Environment Modeling · Neural Networks · Variational Autoencoder · Markov Decision Processes · Exploration · Artificial Experience-Replay

1 Introduction

Reinforcement learning (RL) is a field of research that has quickly become one of the most promising branches of machine learning algorithms to solve artificial general intelligence [2,10,12,16]. There have been several breakthroughs in reinforcement learning in recent years for relatively simple environments [6,14,15,21], but no algorithms are capable of human performance in situations where complex policies must be learned. Due to this, a number of open research questions remain in reinforcement learning. It is possible that many of the problems can be resolved with algorithms that adequately accounts for planning, exploration, and memory at different time-horizons.

In current state-of-the-art RL algorithms, long-horizon RL tasks are difficult to master because there is as of yet no optimal exploration algorithm that is

capable of proper state-space pruning. Exploration strategies such as ϵ-greedy is widely used in RL, but cannot find an adequate exploration/exploitation balance without significant hyperparameter-tuning. Environment modeling is a promising exploration technique where the goal is for the model to imitate the behavior of the target environment. This limits the required interaction with the target environment, enabling nearly unlimited access to exploration without the cost of exhausting the target environment. In addition to environment-modeling, a balance between exploration and exploitation must be accounted for, and it is, therefore, essential for the environment model to receive feedback from the RL agent.

By combining the ideas of variational autoencoders with deep RL agents, we find that it is possible for agents to learn optimal policies using only generated training data samples. The approach is presented as the dreaming variational autoencoder. We also show a new learning environment, Deep Maze, that aims to bring a vast set of challenges for reinforcement learning algorithms and is the environment used for testing the DVAE algorithm.

This paper is organized as follows. Section 3 briefly introduces the reader to preliminaries. Section 4 proposes *The Dreaming Variational Autoencoder* for environment modeling to improve exploration in RL. Section 5 introduces the Deep Maze learning environment for exploration, planning and memory management research for reinforcement learning. Section 6 shows results in the Deep Line Wars environment and that RL agents can be trained to navigate through the deep maze environment using only artificial training data.

2 Related Work

In machine learning, the goal is to create an algorithm that is capable of constructing a model of some environment accurately. There is, however, little research in *game* environment modeling in the scale we propose in this paper. The primary focus of recent RL research has been on the value and policy aspect of RL algorithm, while less attention has been put into perfecting environment modeling methods.

In 2016, the work in [3] proposed a method of deducing the Markov Decision Process (MDP) by introducing an adaptive exploration signal (pseudo-reward), which was obtained using deep generative model. Their method was to compute the Jacobian of each state and used it as the pseudo-reward when using deep neural networks to learn the state-generalization.

Xiao et al. proposed in [22] the use of generative adversarial networks (GAN) for model-based reinforcement learning. The goal was to utilize GAN for learning dynamics of the environment in a short-horizon timespan and combine this with the strength of far-horizon value iteration RL algorithms. The GAN architecture proposed illustrated near authentic generated images giving comparable results to [14].

In [9] Higgins et al. proposed DARLA, an architecture for modeling the environment using β-VAE [8]. The trained model was used to extract the optimal

policy of the environment using algorithms such as DQN [15], A3C [13], and Episodic Control [4]. DARLA is to the best of our knowledge, the first algorithm to properly introduce learning without access to the target environment during training.

Buesing et al. recently compared several methods of environment modeling, showing that it is far better to model the state-space then to utilize Monte-Carlo rollouts (RAR). The proposed architecture, state-space models (SSM) was significantly faster and produced acceptable results compared to auto-regressive (AR) methods. [5]

Ha and Schmidhuber proposed in [7] *World Models*, a novel architecture for training RL algorithms using variational autoencoders. This paper showed that agents could successfully learn the environment dynamics and use this as an exploration technique requiring no interaction with the target domain.

3 Background

We base our work on the well-established theory of reinforcement learning and formulate the problem as a MDP [20]. An MDP contains $(\mathcal{S}, \mathcal{A}, \mathcal{T}, r)$ pairs that define the environment as a model. The state-space, $\mathcal{S}$ represents all possible states while the action-space, $\mathcal{A}$ represents all available actions the agent can perform in the environment. $\mathcal{T}$ denotes the transition function $(\mathcal{T} : \mathcal{S} \times \mathcal{A} \to \mathcal{S})$, which is a mapping from state $s_t \in \mathcal{S}$ and action $a_t \in \mathcal{A}$ to the future state s_{t+1}. After each performed action, the environment dispatches a reward signal, $\mathcal{R} : \mathcal{S} \to r$.

We call a sequence of states and actions a *trajectory* denoted as $\tau = (s_0, a_0, \ldots, s_t, a_t)$ and the sequence is sampled through the use of a stochastic policy that predicts the optimal action in any state: $\pi_\theta(a_t|s_t)$, where π is the policy and θ are the parameters. The primary goal of the reinforcement learning is to *reinforce* good behavior. The algorithm should try to learn the policy that maximizes the total expected discounted reward given by, $\mathcal{J}(\pi) = \mathbb{E}_{(s_t, a_t) \sim p(\pi)} \left[\sum_{i=0}^{T} \gamma^i \mathcal{R}(s_i) \right]$ [15].

4 The Dreaming Variational Autoencoder

The Dreaming Variational Autoencoder (DVAE) is an end-to-end solution for generating probable future states $\hat{s}_{t+n}$ from an arbitrary state-space $\mathcal{S}$ using state-action pairs explored prior to s_{t+n} and a_{t+n}.

The DVAE algorithm, seen in Figure 1 works as follows. First, the agent collects experiences for utilizing experience-replay in the *Run-Agent* function. At this stage, the agent explores the state-space guided by a Gaussian distributed policy. The agent acts, observes, and stores the observations into the experience-replay buffer $\mathcal{D}$. After the agent reaches terminal state, the DVAE algorithm encodes state-action pairs from the replay-buffer D into probable future states. This is stored in the replay-buffer for artificial future-states $\hat{D}$.
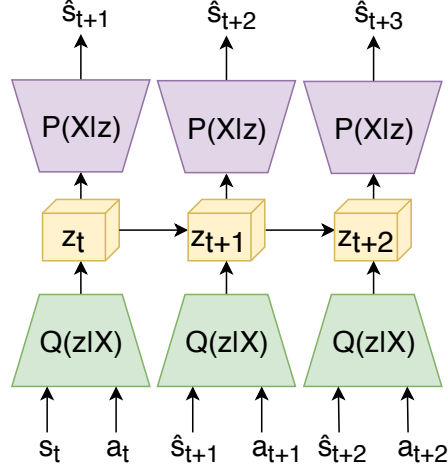
Fig. 1: Illustration of the DVAE model. The model consumes state and action pairs, yielding the input encoded in latent-space. Latent-space can then be decoded to a probable future state. $\mathcal{Q}(z|X)$ is the encoder, z_t is latent-space, and $\mathcal{P}(X|z)$ is the decoder. DVAE can also use LSTM to better learn longer sequences in continuous state-spaces.

Table 1: DVAE algorithm for generating states using $\mathcal{T}_\theta$ versus the real transition function $\mathcal{T}$. First, a real state is collected from the replay-memory. DVAE can then produce new states from current the trajectory τ using the state-action pairs. θ represent the trainable model parameters.
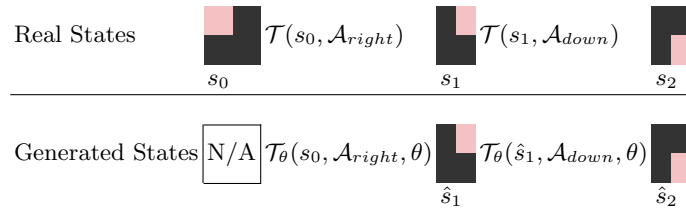
Algorithm 1 The Dreaming Variational Autoencoder

1: Initialize replay memory $\mathcal{D}$ and $\check{\mathcal{D}}$ to capacity $\mathcal{N}$
2: Initialize policy π_θ
3: **function** RUN-AGENT($\mathcal{T}$, $\mathcal{D}$)
4:     **for** i = 0 to N_EPISODES **do**
5:         Observe starting state, $s_0 \sim \mathcal{N}(0, 1)$
6:         **while** s_t not TERMINAL **do**
7:             $a_t \leftarrow \pi_\theta(s_t = s)$
8:             $s_{t+1}, r_t, terminal_t \leftarrow \mathcal{T}(s_t, a_t)$
9:             Store experience into replay buffer $\mathcal{D}(s_t, a_t, r_t, s_{t+1}, terminal_t)$
10:            $s_t \leftarrow s_{t+1}$
11:         **end while**
12:     **end for**
13: **end function**
14: Initialize encoder $\mathcal{Q}(z|X)$
15: Initialize decoder $\mathcal{P}(X|z)$
16: Initialize DVAE model $\mathcal{T}_\theta = \mathcal{P}(X|\mathcal{Q}(z|X))$
17: **function** DVAE
18:     **for** d_i in D **do**
19:         $s_t, a_t, r_t, s_{t+1} \leftarrow d_i$ $\triangleright$ Expand replay buffer pair
20:         $X_t \leftarrow s_t, a_t$
21:         $z_t \leftarrow \mathcal{Q}(X_t)$ $\triangleright$ Encode X_t into latent-space
22:         $\hat{s}_{t+1} \leftarrow \mathcal{P}(z_t)$ $\triangleright$ Decode z_t into probable future state
23:         Store experience into artificial replay buffer $\check{\mathcal{D}}(\hat{s}_t, a_t, r_t, \hat{s}_{t+1}, terminal_t)$
24:         $\hat{s}_t = \hat{s}_{t+1}$
25:     **end for**
26:     **return** $\check{\mathcal{D}}$
27: **end function**

Table 1 illustrates how the algorithm can generate sequences of artificial trajectories using $\mathcal{T}_\theta = \mathcal{P}(X|\mathcal{Q}(z|X))$, where $z = \mathcal{Q}(z|X)$ is the encoder, and $\mathcal{T}_\theta = \mathcal{P}(X|z)$ is the decoder. With state s_0 and action $\mathcal{A}_{right}$ as input, the algorithm generates state $\hat{s}_1$ which in the table can be observed is similar to the real state s_1. With the next input, $\mathcal{A}_{down}$, the DVAE algorithm generates the next state $\hat{s}_2$ which again can be observed to be equal to s_2. Note that this is without ever observing state s_1. Hence, the DVAE algorithm needs to be initiated with a state, e.g. s_0, and actions follows. It then generates (dreams) next states,

The requirement is that the environment must be partially discovered so that the algorithm can learn to behave similarly to the target environment. To predict a trajectory of three timesteps, the algorithm does nesting to generate the whole sequence: $\tau = \hat{s}_1, a_1, \hat{s}_2, a_2, \hat{s}_3, a_3 = \mathcal{T}_\theta(\mathcal{T}_\theta(\mathcal{T}_\theta(s_0, \mathcal{A}_{rnd}), \mathcal{A}_{rnd}), \mathcal{A}_{rnd})$. The algorithm does this well in early on, but have difficulties with long sequences beyond eight in continuous environments.

5 Environments

The DVAE algorithm was tested on two game environments. The first environment is Deep Line Wars [1], a simplified Real-Time Strategy game. We introduce Deep Maze, a flexible environment with a wide range of challenges suited for reinforcement learning research.

5.1 The Deep Maze Environment

The Deep Maze is a flexible learning environment for controlled research in exploration, planning, and memory for reinforcement learning algorithms. Maze solving is a well-known problem, and is used heavily throughout the RL literature [20], but is often limited to small and fully-observable scenarios. The Deep Maze environment extends the maze problem to over 540 unique scenarios including Partially-Observable Markov Decision Processes (POMDP). Figure 2 illustrates a small subset of the available environments for Deep Maze, ranging from small-scale MDP's to large-scale POMDP's. The Deep Maze further features custom game mechanics such as relocated exits and dynamically changing mazes.

The game engine is modularized and has an API that enables a flexible tool set for third-party scenarios. This extends the capabilities of Deep Maze to support nearly all possible scenario combination in the realm of maze solving.[1]

State Representation RL agents depend on sensory input to evaluate and predict the best action at current timestep. Preprocessing of data is essential so that agents can extract features from the input. For this reason, Deep Maze has built-in state representation for RGB Images, Grayscale Images, and raw state matrices.

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[1] The Deep Maze is open-source and publicly available at `https://github.com/CAIR/deep-maze`.

(a) A Small, Fully Observable MDP

(b) A Large, Fully Observable MDP

(c) Partially Observable MDP having a vision distance of 3 tiles

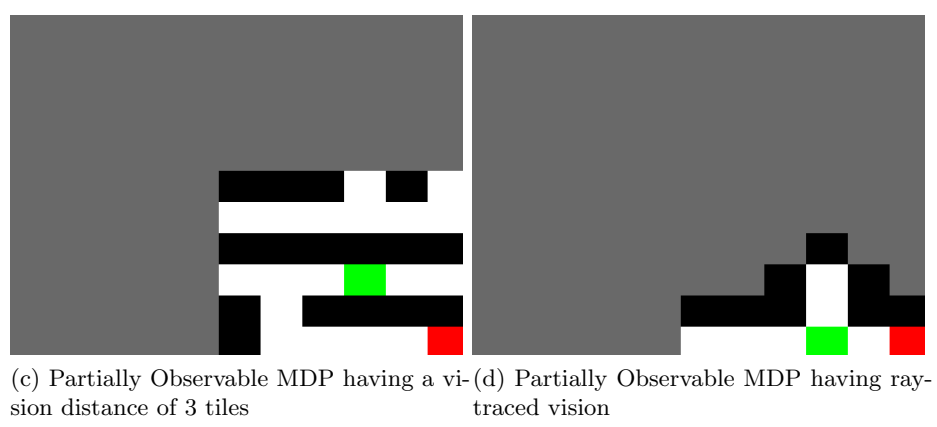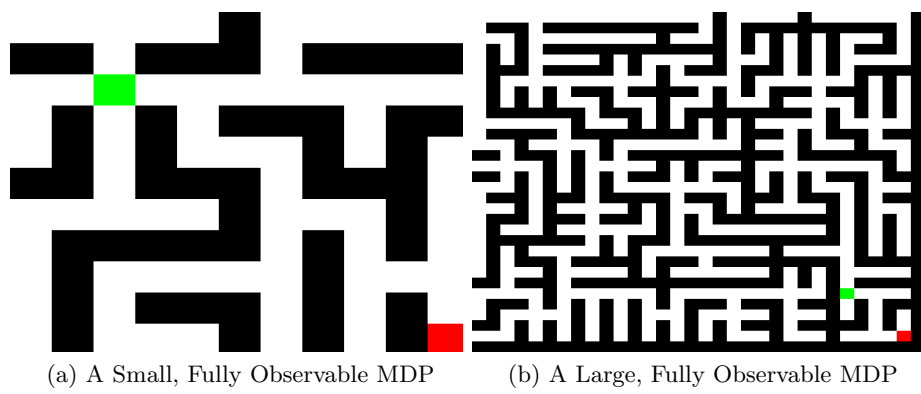(d) Partially Observable MDP having ray-traced vision

Fig. 2: Overview of four distinct MDP scenarios using Deep Maze.

Scenario Setup The Deep Maze learning environment ships with four scenario modes: (1) Normal, (2) POMDP, (3) Limited POMDP, and (4) Timed Limited POMDP.

The first mode exposes a seed-based randomly generated maze where the state-space is modeled as an MDP. The second mode narrows the state-space observation to a configurable area around the player. In addition to radius based vision, the POMDP mode also features ray-tracing vision that better mimic the sight of a physical agent. The third and fourth mode is intended for memory research where the agent must find the goal in a limited number of time-steps. In addition to this, the agent is presented with the solution but fades after a few initial time steps. The objective is the for the agent to remember the solution to find the goal. All scenario setups have a variable map-size ranging between 2×2 and 56×56 tiles.

5.2 The Deep Line Wars Environment

The Deep Line Wars environment was first introduced in [1]. Deep Line Wars is a real-time strategy environment that makes an extensive state-space reduction to enable swift research in reinforcement learning for RTS games.

Fig. 3: The Graphical User Interface of the Deep Line Wars environment.

The game objective of Deep Line Wars is to invade the enemy player with mercenary units until all health points are depleted, see Figure 3). For every friendly unit that enters the far edge of the enemy base, the enemy health pool is reduced by one. When a player purchases a mercenary unit, it spawns at a random location inside the edge area of the buyers base. Mercenary units automatically move towards the enemy base. To protect the base, players can

construct towers that shoot projectiles at the opponents mercenaries. When a mercenary dies, a fair percentage of its gold value is awarded to the opponent. When a player sends a unit, the income is increased by a percentage of the units gold value. As a part of the income system, players gain gold at fixed intervals.

6 Experiments

6.1 Deep Maze Environment Modeling using DVAE

The DVAE algorithm must be able to generalize over many similar states to model a vast state-space. DVAE aims to learn the transition function, bringing the state from s_t to $s_{t+1} = \mathcal{T}(s_t, a_t)$. We use the deep maze environment because it provides simple rules, with a controllable state-space complexity. Also, we can omit the importance of reward for some scenarios.

We trained the DVAE model on two *No-Wall Deep Maze* scenarios of size 2×2 and 8×8. For the encoder and decoder, we used the same convolution architecture as proposed by [17] and trained for 5000 epochs for 8×8 and 1000 epochs for 2×2 respectively. For the encoding of actions and states, we concatenated the flattened state-space and action-space, having a fully-connected layer with ReLU activation before calculating the latent-space. We used the Adam optimizer [11] with a learning-rate of 1e-08 to update the parameters.

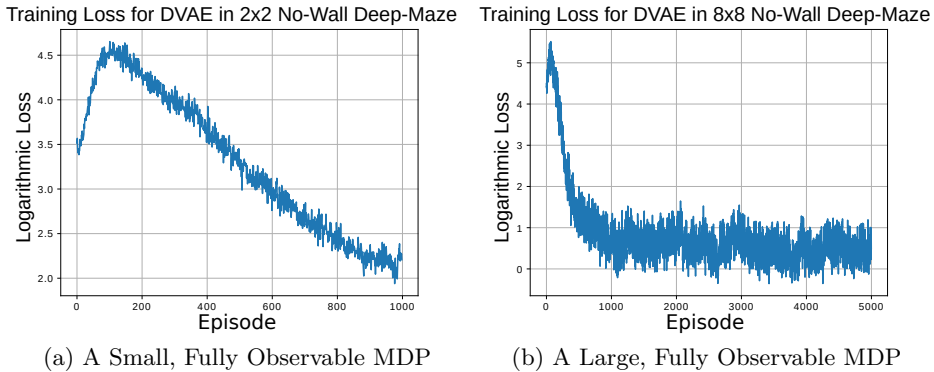(a) A Small, Fully Observable MDP   (b) A Large, Fully Observable MDP

Fig. 4: The training loss for DVAE in the 2×2 No-Wall and 8×8 Deep Maze scenario. The experiment is run for a total of 1000 (5000 for 8×8) episodes. The algorithm only trains on 50% of the state-space to the model for the 2×2 environment while the whole state-space is trainable in the 8×8 environment.

Figure 4 illustrates the loss of the DVAE algorithm in the No-Wall Deep Maze scenario. In the 2×2 scenario, DVAE is trained on only 50% of the state space, which results in noticeable graphic artifacts in the prediction of future

states, see Figure 5. Because the 8×8 environment is fully visible, we see in Figure 6 that the artifacts are exponentially reduced.

Fig. 5: For the 2×2 scenario, only 50% of the environment is explored, leaving artifacts on states where the model is uncertain of the transition function. In more extensive examples, the player disappears, teleports or gets stuck in unexplored areas.

Table 2: Results of the deep maze 11×11 and 21×21 environment, comparing DQN [15], TRPO [18], and PPO [19]. The optimal path yields performance of 100% while no solution yields 0%. Each of the algorithms ran 10000 episodes for both map-sizes. The last number represents at which episode the algorithm converged.

Algorithm	Avg Performance 11×11	Avg Performance 21×21
DQN-$\hat{\mathcal{D}}$	94.56% @ 9314	64.36% @ N/A
TRPO-$\hat{\mathcal{D}}$	96.32% @ 5320	78.91% @ 7401
PPO-$\hat{\mathcal{D}}$	98.71% @ 3151	89.33% @ 7195
DQN-$\mathcal{D}$	98.26% @ 4314	84.63% @ 8241
TRPO-$\mathcal{D}$	99.32% @ 3320	92.11% @ 4120
PPO-$\mathcal{D}$	99.35% @ 2453	96.41% @ 2904

6.2 Using $\hat{\mathcal{D}}$ for RL Agents in Deep Maze

The goal of this experiment is to observe the performance of RL agents using the generated experience-replay $\hat{\mathcal{D}}$ from Figure 1 in Deep Maze environments of size 11×11 and 21×21. In Table 2, we compare the performance of DQN [14], TRPO [18], and PPO [19] using the DVAE generated $\hat{\mathcal{D}}$ to tune the parameters.

Figure 7 illustrates three maze variations of size 11×11, where the AI has learned the optimal path. We see that the best performing algorithm, PPO [19] beats DQN and TRPO using either $\hat{\mathcal{D}}$ or $\mathcal{D}$. The DQN-$\hat{\mathcal{D}}$ agent did not converge in the 21×21 environment, but it is likely that value-based algorithms could struggle with graphical artifacts generated from the DVAE algorithm. These artifacts significantly increase the state-space so that direct-policy algorithms could perform better.
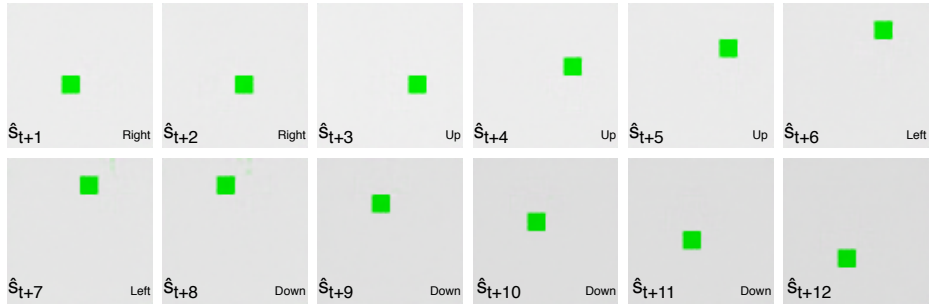
Fig. 6: Results of 8×8 Deep Maze modeling using the DVAE algorithm. To simplify the environment, no reward signal is received per iteration. The left caption describes current state, s_t, while the right caption is the action performed to compute, $s_{t+1} = \mathcal{T}(s_t, a_t)$.
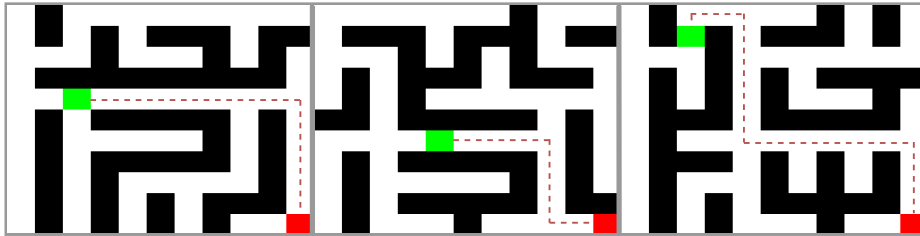

Fig. 7: A typical deep maze of size 11×11. The lower-right square indicates the goal state, the dotted-line indicates the optimal path, while the final square represents the player's current position in the state-space. The controller agent is DQN, TRPO, and PPO (from left to right).

6.3   Deep Line Wars Environment Modeling using DVAE

The DVAE algorithm works well in more complex environments, such as the Deep Line Wars game environment [1]. Here, we expand the DVAE algorithm with LSTM to improve the interpretation of animations, illustrated Figure 1.
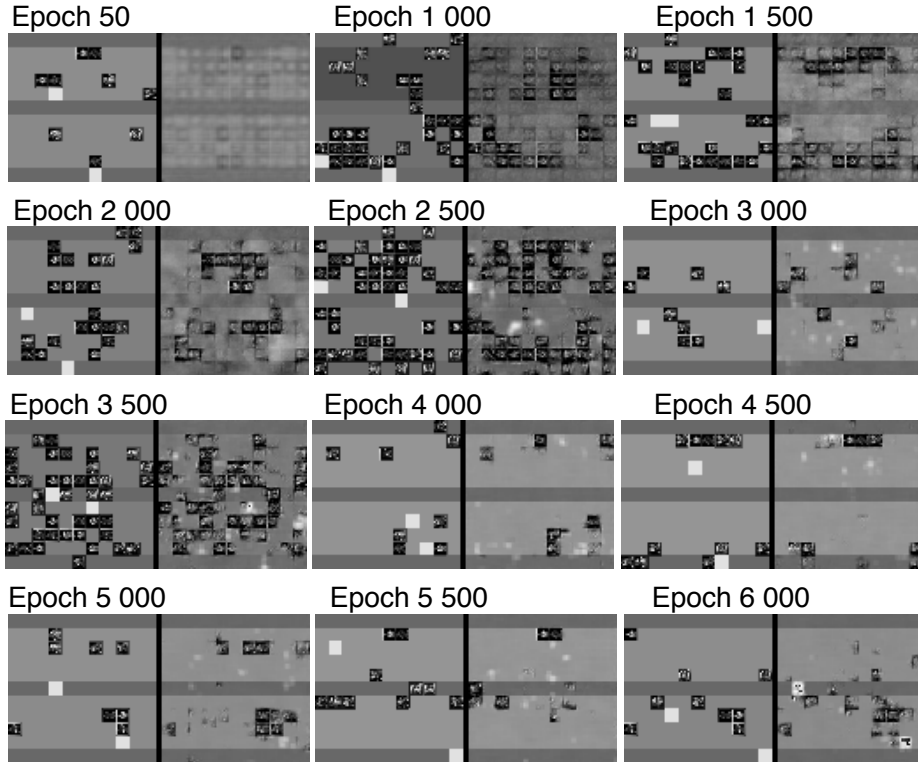

Fig. 8: The DVAE algorithm applied to the Deep Line Wars environment. Each epoch illustrates the quality of generated states in the game, where the left image is real state s and the right image is the generated state $\hat{s}$.

Figure 8 illustrates the state quality during training of DVAE in a total of 6000 episodes (epochs). Both players draw actions from a Gaussian distributed policy. The algorithm understands that the player units can be located in any tiles after only 50 epochs, and at 1000 we observe the algorithm makes a more accurate statement of the probability of unit locations (i.e., some units have increased intensity). At the end of the training, the DVAE algorithm is to some degree capable of determining both towers, and unit locations at any given time-step during the game episode.

7 Conclusion and Future Work

This paper introduces the *Dreaming Variational Autoencoder* (DVAE) as a neural network based generative modeling architecture to enable exploration in environments with sparse feedback. The DVAE shows promising results in modeling simple non-continuous environments. For continuous environments, such as Deep Line Wars, DVAE performs better using a recurrent neural network architecture (LSTM) while it is sufficient to use only a sequential feed-forward architecture to model non-continuous environments such as Chess, Go, and Deep Maze.

There are, however, several fundamental issues that limit DVAE from fully modeling environments. In some situations, exploration may be a costly act that makes it impossible to explore all parts of the environment in its entirety. DVAE cannot accurately predict the outcome of unexplored areas of the state-space, making the prediction blurry or false.

Reinforcement learning has many unresolved problems, and the hope is that the Deep Maze learning environment can be a useful tool for future research. For future work, we plan to expand the model to model the reward function $\hat{\mathcal{R}}$ using inverse reinforcement learning. DVAE is an ongoing research question, and the goal is that reinforcement learning algorithms could utilize this form of *dreaming* to reduce the need for exploration in real environments.

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