Hallucinating Value: A Pitfall of Dyna-style Planning with Imperfect Environment Models

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Abstract
Dyna-style reinforcement learning (RL) agents improve sample efficiency over model-free RL agents by updating the value function with simulated experience generated by an environment model. However, it is often difficult to learn accurate models of environment dynamics, and even small errors may result in failure of Dyna agents. In this paper, we investigate one type of model error: hallucinated states. These are states generated by the model, but that are not real states of the environment. We present the Hallucinated Value Hypothesis (HVH): updating values of real states towards values of hallucinated states results in misleading state-action values which adversely affect the control policy. We discuss and evaluate four Dyna variants; three which update real states toward simulated – and therefore potentially hallucinated – states and one which does not. The experimental results provide evidence for the HVH thus suggesting a fruitful direction toward developing Dyna algorithms robust to model error.

1. Introduction
Reinforcement learning (RL) is an approach to solving sequential decision-making problems that has had notable successes in recent years. It has been used to train agents that play arcade games (Bellemare et al., 2013) at human level performance (Mnih et al., 2015) and to develop robotic hands with human-like dexterity (Andrychowicz et al., 2018). These successes have come at a cost: large data requirements (e.g., DQN requires 200 million samples to learn control policies for games). Such sample requirements make RL an unsolvable solution for many realistic settings, and a key challenge is developing sample efficient RL methods. One promising approach to address this challenge is Dyna (Sutton, 1990) — an architecture where real experience is supplemented with simulated experience.

In Dyna, agents use a model of their environment to simulate experience. By updating their value functions with this data, in a process known as planning, agents may learn improved control policies using less real data than model-free RL agents. Early work on Dyna considered environments with deterministic dynamics and finite state spaces (Sutton, 1990; 1991). In such settings, learning perfectly accurate environment models is possible: store a table of states and actions and record the next observed states for a given state and action. Generally, however, learning perfect environment models is difficult, if not impossible. Moreover, emerging evidence suggests that even small model errors can result in large errors in the value function (van Hasselt et al., 2019).

Most work investigating how to minimise model error has primarily considered errors due to model rollouts. In rollouts, a model’s predictions are iteratively fed back to itself to generate a simulated trajectory. Even small inaccuracies in predictions can compound and render a trajectory useless for planning as the final predictions bear little resemblance to any plausible future as shown by Talvitie (2014; 2017). To address this, Talvitie proposed Hallucinated Replay: training a model on its own imperfect predictions to minimise compounding error. Other work reduced error due to iteration by learning a model in a latent space (Ke et al., 2019), rather than on observations. Improving model accuracy, however, is unlikely to resolve failure in Dyna. For example, Holland et al. (2018) showed that even with a learning curriculum to minimise compounding error, imperfections in model predictions eventually overwhelm any signal in simulated trajectories and value function updates with this data is detrimental to learning. Another strategy, therefore, is to dynamically truncate rollouts based on uncertainty or errors in the model (Buckman et al., 2018).

In this paper, we investigate a phenomenon where model errors harm performance not due to iteration but rather from value function updates bootstrapping off values of hallucinated states. Hallucinated states are simulated states from the model that do not correspond to real states of the environment. The values of these states are never updated directly from real experience because they are not reachable by the agent. Rather, their values are essentially arbitrary, depending on value function initialisation and how the function approximator generalises. As a result, when updates are performed using simulated experience, the value of real states may be contaminated by the arbitrary values of hallucinated states. In turn, this may mislead the control policy. We propose the Hallucinated Value Hypothesis:
Planning updates that result in the values of real states being updated towards the values of simulated states impedes learning of the control policy.

In the following sections, we discuss how variants of Dyna can suffer from this problem because they update real states to simulated states. We then propose a new algorithm, Multi-step Predecessor Dyna, which is designed to avoid such updates. We introduce an environment to test the hypothesis and show that previous variants of Dyna fail when the model is imperfect whereas our algorithm does not. We then test the algorithms on three classic benchmark environments and find even in these environments the phenomenon persists.

2. Background

RL is an approach to solving problems formalised by a Markov Decision Process (MDP). MDPs are defined by the tuple $(S, A, r, p, γ)$. $S$ is a set of states, $A$ is a set of actions, $r : S × A × S → ℜ$ is a reward function defining the reward received upon taking a given action in a given state, $p : S × A × S → [0, 1]$ is a function defining the transition dynamics of the MDP, and $γ ∈ [0, 1]$ is a discount parameter influencing how far-sighted or myopic the agent is. At time $t$, the agent is in a state $s_t ∈ S$. It takes action $a_t ∈ A$ which transitions it to a new state $s_{t+1} ∈ S$ with probability $p(s_t, a_t, s_{t+1})$. It also receives reward $r_t = r(s_t, a_t, s_{t+1})$.

The agent selects actions according to a policy $π : S × A → [0, 1]$, where $π(·|s)$ is a distribution over actions in state $s$. The agent’s goal is to learn a policy which maximises $V^π(s) = \sum_{t=0}^{∞} \gamma^t r_t$ where $r_t$ is the reward received upon taking a given action in a given state.

Q-learning (Watkins & Dayan, 1992) is used to learn a policy by learning a state-action value function. For a policy $π$, the state-action value function is $Q^π(s, a) = \mathbb{E}[r(s, a, s_{t+1}) + γ V^π(s_{t+1})]$, the expected discounted value in the long-run of taking action $a$ in state $s$ and following policy $π$ thereafter. As the agent interacts with the environment experiencing transitions $(s_t, a_t, r_t, s_{t+1})$ an update $Q(s_t, a_t) ← Q(s_t, a_t) + α(r_t + γ \max_a Q(s_{t+1}, a) - Q(s_t, a))$ is performed. This updates the value function towards $Q^π$, the value function of the optimal policy $π^∗$. Q-learning is a model-free algorithm, i.e., it learns only from data gathered by interacting with the environment.

Model-based approaches use a model to learn a policy. The Dyna framework (Sutton, 1990) is one approach to model-based RL in which learning, planning, and acting are integrated. For example, in Dyna-Q an agent first does a Q-learning update on real experience. Then it performs planning updates in which it 1) draws a state $s_i$ from its previous experience; 2) selects action $a_i$ to perform in $s_i$ using its current policy; 3) uses its model to generate next state $\hat{s}_{i+1}$ and reward $\hat{r}_i$ (that indicates a simulated variable); and 4) performs the Q-learning update on $(s_i, a_i, \hat{r}_i, \hat{s}_{i+1})$. These extra updates allow Dyna-Q to learn a good policy with less real data than Q-learning. This is one variant of Dyna; we will discuss other choices in Section 4.

3. Motivating the Hypothesis

Here we present an example motivating the HVH. Figure 1 (a) shows Borderworld, a 2D navigation environment. State is represented by the tuple $(x, y)$ indicating the agent’s position, and the actions North, East, South, West result in the agent moving in the respective cardinal direction. Reward is 1 on transitioning into the goal state and 0 elsewhere. The key feature of Borderworld is a border of unreachable states. These states form a set $S_B$, while the reachable states form a set $S_R$. In the underlying MDP there are no transitions from $S_B$ to $S_R$. However, as we describe below, imperfect models may predict such transitions.

Suppose a neural network is trained to predict transition dynamics on Borderworld. In most states taking an action results in a deterministic change to the agent’s position. For example, taking the action West from $(3, 1)$ results in the agent’s position changing to $(2, 1)$. The dynamics of West are similar across most of the environment, and so a neural network will likely generalise this behaviour even to states beside the border, i.e., it may generate simulated state $(\hat{x}, \hat{y})$ where $\hat{x}$ is in the border (Figure 1 (b)). Does this small error really impact the performance of a Dyna-Q agent?

Consider the transition in Figure 1 (b). The value of $Q(s_t, \text{West})$ is updated towards the target $\hat{r}_t + γ \max_a Q(\hat{s}_{t+1}, a)$. However, this target can be misleading because the value $Q(\hat{s}_{t+1}, a)$ is not updated with real experience and is essentially arbitrary. Suppose the Q-function is optimistically initialised so that unvisited states have high value. The value of $\max_a Q(\hat{s}_{t+1}, a)$ will be large, which will, in turn, raise the value of $Q(s_t, \text{West})$. This may cause the agent to prefer moving to the wall, rather than moving toward the goal. Furthermore, the erroneous high value of the simulated state cannot be corrected through real experience as the agent cannot reach $\hat{s}_{t+1}$ to change its value.

This example highlights that Dyna algorithms which update real state values towards simulated state values may be brittle in the face of model error. In a simple example such as Borderworld, the agent may eventually correct its model error; it is, after all, driven to experience states where its model is incorrect. However, in more complex environments it is unreasonable to expect the model to ever correct all of its errors. In Section 5.2 we observe negative effects from hallucinated values in several standard benchmark domains.
We also see that these errors are persistent and do not resolve on their own. In the next section, we develop a design space of Dyna algorithms and discuss their implications with respect to the HVH.

4. A Design Space of Dyna Algorithms

Dyna is a flexible framework which admits a variety of implementations. In this work we focus on two design choices that provide four Dyna variants: 1) if the model is used to simulate dynamics forward or backward in time; 2) whether the planning TD updates are one-step or multi-step. We explain these choices below but otherwise make standard choices for Dyna: updating with real experience, using prioritization, and simulating all actions during planning.

The four algorithms are variations of Algorithm 1. Real environment data is used to update the action-value functions and the environment model (lines 7-9). The real experience is added to a search-control queue \( P \), with priority \( |\delta| \) (line 10). The transitions in this queue are used to perform \( N \) planning steps (lines 11 - 15). In each planning step the highest priority transition is popped off the queue (line 12), the model \( M \) is used to generate simulated transitions (line 13), and these transitions are used to update action-values (line 14). Finally, these simulated transitions are added to the queue with a priority equal to their TD error multiplied by \( \beta^n \) (line 15), \( \beta \in [0, 1] \) is a hyperparameter we introduce that controls the rate of decay of the priority and \( n \) is the number of times the model has been iterated to extend the length of the trajectory. Intuitively, this prevents highly iterated trajectories from being added to \( P \) thereby mitigating compounding model error. In Subsection 4.3 we discuss the implications of \( \beta \) on the flavours of Dyna we study.

This Dyna algorithm is standard except for \( \beta \) and that entire tuples are stored on the queue with an explicit parameter \( n \). This storing of tuples is a necessary modification to consider multi-step updates with Dyna, as described in Section 4.2.

4.1. Successor vs Predecessor Models

The first design choice we explore is whether the model simulates environment dynamics forward in time or backward in time. A model that simulates environment dynamics forward in time is a successor model. From state \( s_t \) given action \( a_t \), the successor model generates a successor state \( \hat{s}_{t+1} \) and reward \( \hat{r}_t \). Conversely, a predecessor model simulates dynamics backward in time. From state \( s_t \), given action \( \hat{a}_{t-1} \), a predecessor state \( \hat{s}_{t-1} \) and reward \( \hat{r}_{t-1} \) are generated.

We can feedback a model’s predictions to itself in order to generate subsequent predictions. This leads to an iteration process in which we generate trajectories that radiate forward or backwards from a state. Suppose we use a successor model in Algorithm 1, and during planning a tuple \((s_t, a_t, r_t, s_{t+1}, n = 0)\) is popped from \(P\) (\(n = 0\) indicates this trajectory has not been iterated). The model could be queried to yield the first iterated transition \((s_t, a_t, r_t, \hat{s}_{t+1}, \hat{a}_{t+1}, \hat{r}_{t+1}, \hat{s}_{t+2}, \hat{a}_{t+2}, \hat{r}_{t+2}, \hat{s}_{t+3}, n = 1)\) which could be added to \(P\). This tuple may be popped in the next planning step and the model queried to yield a second iterated transition \((s_t, a_t, r_t, \hat{s}_{t+1}, \hat{a}_{t+1}, \hat{r}_{t+1}, \hat{s}_{t+2}, \hat{a}_{t+2}, \hat{r}_{t+2}, \hat{s}_{t+3}, n = 2)\). This process may be continued to generate tuples for all possible actions yielding trajectories that radiate from \( s_t \).

We can also examine tuples generated when iterating a predecessor model. Again, suppose the first tuple is popped from the queue is \((s_t, a_t, r_t, s_{t+1}, n = 0)\). The predecessor model produces an iterated transition,
Multi-step TD Updates

whereas the multi-step TD update would update the value of \( I \) backwards in time. Pan et al. (2018) show the utility of iterating model predictions in this manner is typical of many Dyna algorithms. Some algorithms use successor models with iteration (Gu et al., 2016) while others such as Prioritized Sweeping (Moore & Atkeson, 1993; Peng & Williams, 1993) use a predecessor model to iterate predictions backwards in time. Pan et al. (2018) show the utility of iterating backward in time compared to other approaches.

4.2. One-step vs Multi-step TD Updates

The second choice we examine is if the algorithm performs one-step TD updates or a multi-step TD updates. A one-step update bootstraps immediately on the next state, whereas a multi-step update sums up multiple rewards until finally bootstrapping on a state multiple steps into the future.

To see how this choice manifests in Dyna, consider a successor model starting with \( (s_t, a_t, r_t, s_{t+1}, n = 0) \). From \( s_{t+1} \) the successor model produces the trajectory, \( (s_t, a_t, r_t, s_{t+1}, \hat{a}_{t+1}, \hat{r}_{t+1}, \hat{s}_{t+2}, n = 1) \). The one-step TD update would be from \( s_{t+1} \) to \( \hat{s}_{t+2} \):

\[
Q(s_{t+1}, \hat{a}_{t+1}) \leftarrow Q(s_{t+1}, \hat{a}_{t+1}) + \\
\alpha(\hat{r}_{t+2} + \gamma \max_{a} Q(\hat{s}_{t+2}, a) - Q(s_{t+1}, \hat{a}_{t+1}))
\]

The multi-step TD update, however, would update \( s_t \) to \( \hat{s}_{t+2} \), with the discounted sum of rewards in-between:

\[
Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \\
\alpha(r_{t+1} + \gamma \hat{r}_{t+2} + \gamma^2 \max_{a} Q(\hat{s}_{t+2}, a) - Q(s_t, a_t))
\]

Imagine this tuple is iterated again. The one-step TD update would update the value of \( \hat{s}_{t+2} \) towards the value of \( \hat{s}_{t+3} \) whereas the multi-step TD update would update the value of \( s_t \) towards the value of \( \hat{s}_{t+2} \).

Both update approaches use the same generated trajectory, but use it differently. One-step TD performs all the one-step updates along the trajectory, updating the values for all the states in the trajectory. Multi-step TD performs a one-step update, then a two-step update, then a three-step update and so on, all updating only state \( s_t \). Note, we have to use importance sampling to weight multi-step TD updates (Sutton & Barto, 2018). We do not include importance weights in this section to make the updates simpler to understand.

4.3. The Four Dyna Variants

The four variants are identical except in parts of the planning loop (Lines 11 - 15 of Algorithm 1), so we focus our discussion below on the differences in planning. When describing each algorithm we summarize related work of that type of algorithm. We summarize the literature in Table 1. Moreover, Figure 2 visually compares the four algorithms.

**One-step Successor** uses a successor model with one-step TD updates. Suppose a tuple \( T_n = (s_t, a_t, r_t, s_{t+1}, n = 0) \) is popped from \( P \). We use the model \( M \) to extend the trajectory forward in time, yielding \( T_{n+1} = (s_t, a_t, r_t, s_{t+1}, \hat{a}_{t+1}, \hat{r}_{t+1}, \hat{s}_{t+2}, n = 1) \). Then, we do a one-step TD update from \( s_{t+1} \) to \( \hat{s}_{t+2} \). \( T_{n+1} \) is added back to \( P \) and, if the TD-error is sufficiently high, it will be popped off in the future to further extend the trajectory from \( \hat{s}_{t+2} \). In general, given a trajectory of \( n \) steps we update:

\[
Q(s_{t+n}, a_{t+n}) \leftarrow Q(s_{t+n}, a_{t+n}) + \\
\alpha(\hat{r}_{t+n+1} + \gamma \max_{a} Q(s_{t+n+1}, a) - Q(s_{t+n}, \hat{a}_{t+n}))
\]

where the model is used to generate \( \hat{r}_{t+n} \) and \( \hat{s}_{t+n+1} \).

This is one of the simplest strategies, and so variants of it are common (Gu et al., 2016; Holland et al., 2018; Kalweit & Boedecker, 2017). The original Dyna-Q algorithm (Sutton, 1990) similarly uses a successor model and one-step updates, though it does not iterate the model (i.e., \( \beta = 0 \), which results in the priority of trajectories with \( n \geq 1 \) being 0). We can reason about how this approach performs in Borderworld. It may be immediately clear that the problematic transition discussed in Section 3 will be generated — the value of moving toward the border will be erroneously increased as a result of the high value of an unreachable border states. When iterating the model, however, this error may be corrected over time. The model may simulate transitions from border states back to reachable states. As such, the values of hallucinated states are updated during planning. Thus, in Borderworld, it may be possible that hallucinated values eventually cease to be an issue, but this may take a great deal of time, likely harming rather than helping sample complexity.

**Multi-step Successor Dyna** uses a successor model

| Table 1. Previous work corresponding to the four Dyna variants. Multi-step Predecessor Dyna has not been previously proposed. |
|---|---|
| **Predecessor** | **One-step Predecessor (Yao et al., 2009; Buckman et al., 2018)** |
| **Successor** | **One-step Successor (Sutton, 1990; Hollands et al., 2018; Gu et al., 2016; Kalweit & Boedecker, 2017)** |
| **Multi-step Predecessor** | **Multi-step Successor (Peng & Williams, 1993; Moore & Atkeson, 1993; Sutton et al., 2008; Goyal et al., 2019; Pan et al., 2018)** |
| **Multi-step Successor** | **Multi-step Predecessor** |
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Algorithm 2 Planning TD Update

1: Input Trajectory \( T_n = (s_t, a_t, r_t, ..., s_{t+n}) \)
2: for \( a_t \) in \( \mathcal{A} \) do
3:  if Successor then
4:  Simulate dynamics forward \( \mathcal{M}(s_{t+n}, a_t) = \hat{s}_{t+n+1}, \hat{r}_{t+n} \); Let \( T_{n+1} = (s_t, a_t, r_t, ..., s_{t+n}, a_t, \hat{r}_{t+n}, \hat{s}_{t+n+1}) \)
5:  if One-Step then
6:  \( \delta \leftarrow \hat{r}_{t+n} + \gamma \max_{a'} Q(\hat{s}_{t+n+1}, a') - Q(s_{t+n}, a_t) \)
7:  \( Q(s_{t+n}, a_t) \leftarrow Q(s_{t+n}, a_t) + \alpha \delta \)
8:  if Multi-Step then
9:  \( \delta \leftarrow \sum_{k=0}^{n} \gamma^k r_{t+k} + \gamma^{n+1} \max_a Q(\hat{s}_{t+n+1}, a) - Q(s_t, a_t) \)
10:  \( Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \delta \)
11: if Predecessor then
12:  Simulate dynamics backward \( \mathcal{M}(s_t, a_t) = \hat{s}_{t-1}, \hat{r}_{t-1} \); Let \( T_{n+1} = (\hat{s}_{t-1}, a_t, \hat{r}_{t-1}, s_t, ..., s_{t+n}) \)
13:  if One-Step then
14:  \( \delta \leftarrow \hat{r}_{t-1} + \gamma \max_{a'} Q(\hat{s}_{t-1}, a') - Q(s_{t-1}, a_t) \)
15:  \( Q(s_{t-1}, a_t) \leftarrow Q(s_{t-1}, a_t) + \alpha \delta \)
16: if Multi-Step then
17:  \( \delta \leftarrow \sum_{k=0}^{n} \gamma^k r_{t+k} + \gamma^{n+1} \max_a Q(s_{t-1}, a) - Q(s_{t-1}, a_t) \)
18:  \( Q(s_{t-1}, a_t) \leftarrow Q(s_{t-1}, a_t) + \alpha \delta \)
19: return \( T_{n+1}, \delta \)

This multi-step strategy is less common than using one-step updates, but variants of the idea have been explored. Yao et al. (2009) perform Dyna with a linear model and linear value function. They learn a multi-step model that directly predicts the expected reward and state multiple steps in the future, averaged over many timescales. Buckman et al. (2018) also average over many multi-step updates, in this case weighted by a measure of uncertainty on the temporal difference error at each horizon. Outside of Dyna, multi-step updates are a common choice for Q-learning because value information can be quickly propagated.

We can again see, though, that this approach could still suffer from hallucinated values. In Borderworld, the agent can still generate trajectories into the border and update values for real states hallucinated values of the border states. Unlike one-step updates, values of hallucinated states toward will not be corrected as the multi-step update only updates real state values.

One-step Predecessor Dyna uses a predecessor model with one-step updates. The algorithm is similar to One-step Successor Dyna, but with updates using the reverse-dynamics trajectory. After \( n \) iterations backwards with the model from an observed state \( s_t \), we have a trajectory \( \hat{s}_{t-n}, a_{t-n}, \hat{r}_{t-n+1}, \hat{s}_{t-n+1}, ..., \hat{r}_t, s_t, a_t, r_{t+1}, s_{t+1} \). Then the predecessor model is queried, using \( \hat{s}_{t-n} \) and \( a_{t-n} \), to get predecessor state \( \hat{s}_{t-n-1} \) and reward \( \hat{r}_{t-n} \), with complete transition \( \hat{s}_{t-n-1}, a_{t-n-1}, \hat{r}_{t-n-1}, \hat{s}_{t-n} \). The agent then updates with

\[
Q(\hat{s}_{t-n-1}, a_{t-n-1}) \leftarrow Q(\hat{s}_{t-n-1}, a_{t-n-1}) + \alpha (\hat{r}_{t-n} + \gamma \max_a Q(\hat{s}_{t-n}, a) - Q(\hat{s}_{t-n-1}, \hat{a}_{t-n-1}))
\]

The canonical example of Dyna-style planning with predecessor state models is Prioritized Sweeping (Peng & Williams, 1993; Moore & Atkeson, 1993). The core idea of Prioritized Sweeping is, when a state is pulled off of the queue and its value is updated, its predecessors are added to the priority queue. Recent work extends this approach to the function approximation setting (Goyal et al., 2019; Pan et al., 2018). Sutton et al. (2008) used a small modification of this idea for linear models and value functions, by generating predecessor features for each state feature instead of predecessor states.

In this algorithm the value of \( \beta \) plays a key role with respect to whether it suffers from the problem posed in the HVH. If \( \beta > 0 \), this approach can still suffer from hallucinated values, as it updates values of real states using simulated states. For example, consider Borderworld. If the agent is
in state $s_{t} = s$ beside the border, it can generate $\hat{s}_{t-1}$ inside the border and then $\hat{s}_{t-2} = s$ back outside the border. Consequently, when it updates $\hat{s}_{t-2}$ using $\hat{s}_{t-1}$, it will update the value of a real state using a hallucinated state. However, if we prevent it from extending the backwards trajectory further from $\hat{s}_{t-1}$, after the first iteration, there is no chance of updating the value of a real state towards the value of a simulated state. All planning updates only update values of simulated states to values of real states. Precisely this occurs when $\beta = 0$ (and the priority threshold $\rho > 0$) because a trajectory with more than one simulated state will have a priority of zero in the queue. We call the version of this algorithm which generates backwards trajectories greater than length 1 Iterated One-step Predecessor Dyna, and the one which does not generate such trajectories Uniterated One-step Predecessor Dyna.

**Multi-step Predecessor Dyna** uses a predecessor model with multi-step TD updates. A tuple is sampled from the queue $P$, consisting of a reverse trajectory just like One-step Predecessor Dyna. Then, a state $\hat{s}_{n-1}$ and reward $\hat{r}_{t-n-1}$ for action $\hat{a}_{t-n-1}$ are generated. The agent then updates with

$$Q(\hat{s}_{t-n-1}, \hat{a}_{t-n-1}) \leftarrow Q(\hat{s}_{t-n-1}, \hat{a}_{t-n-1}) + \alpha \sum_{i=0}^{n} \gamma^{i} \hat{r}_{t-n+i} + \gamma^{n} \max_{a} Q(s_{t}, a) - Q(s_{t-n}, \hat{a}_{t-n})$$

(4)

Somewhat surprisingly, this fourth variant has not been previously considered; in this work we explore this understudied region of the Dyna design space. The key feature of Multi-step Predecessor Dyna is that the agent only updates towards the values of real states, $\max_{a} Q(s_{t}, a)$. Thus, we hypothesize that Multi-step Predecessor state Dyna will be more robust to model error than the other three variants discussed above, because it does not use hallucinated values in the target and so is not prone to hallucinated value errors. In the next section we experimentally test this hypothesis.

### 5. Experiments

We first conducted controlled experiments on Borderworld. These experiments show clear evidence supporting the HVH: the Dyna algorithms that update values of real states to values of simulated states all fail while the algorithms that do not perform such planning updates succeed. We then conducted experiments on several RL benchmarks where the results again support the HVH.

#### 5.1. Borderworld

Planning updates are problematic if the environment model produces hallucinated states as updating toward these states propagates arbitrary value. To mimic these conditions in Borderworld we introduced error to an otherwise perfect environment model of Borderworld. Specifically, the model generates transitions from real states to hallucinated border states, as in Figure 1b (and from border states to border states). Further, we optimistically initialised the value function so that hallucinated border states have misleading values. We used the algorithms specified in Section 4 with a tabular value function. Figure 3 shows plots of accumulated reward against cumulative real experience. All curves are averages over 10 runs and for the best $\alpha$ of each algorithm.

One-step Successor, Multi-step Successor, and Iterated One-step Predecessor update toward simulated states. The learning curves for these approaches increase slightly early on (while optimism still holds) but then flatten out. This indicates that as the value function is updated, the policy becomes incorrect for solving Borderworld. As we do not see such a failure in model-free Q-learning, the planning updates must be responsible for harming the policy. Heatmaps of $\max_{a} Q(s, a)$ $\forall s \in S$ after 100,000 steps for the three failing algorithms are shown in Figure 4. The plots for these three approaches (top row) all show high values for reachable states near the border. In Borderworld, the only transitions with real reward are those that lead to the goal state in the centre. Therefore, the high values near the border must be the result of planning updates propagating values from border states to real states near the border. When the agent reaches one of these states close to the border instead of taking actions that move it closer to the goal, it takes actions toward the border, chasing hallucinated value.

In contrast, Uniterated One-step Predecessor and Multi-step Predecessor never update toward a simulated state. Their learning curves show superior performance to Q-learning. This indicates these algorithms are robust to this type of model error and that planning has a beneficial effect despite the errors in the model. Indeed, in Figure 4, we do not see contamination of values of real states.

One final interesting phenomenon shown in Figure 4 is that for One-step Successor and Iterated One-step Predecessor, the values of border states are lower than their initialisation values. For these algorithms, after sufficient planning, hallucinated values may be updated to be more similar to those
of real states – eventually they might no longer mislead the agent. However, this may take a long time and the agent will be catastrophically misled in the meantime.

5.2. Reinforcement Learning Benchmarks

We now consider experiments that examine the HVH in more typical settings. First, we did not artificially introduce error to the environment model. Rather, we learned an environment model online from real transitions. Because the model is learned online, it might have the opportunity to correct its errors and eliminate hallucinated value updates (we will see that this does not happen in practice). Second, we did not place any limitations on the initialisation of the agent’s weights. These choices enabled us to explore whether harmful effects of propagating arbitrary values may be observed when the model is not explicitly designed to generate hallucinated states, and when the agent’s weights are not biased in some manner. Our experiments were conducted on Cartpole (Brockman et al., 2016), Puddle World (Degris et al., 2012), and Catcher (Tasfi, 2016). For each algorithm we swept over α (20 randomly selected from range (0, 0.5)) and performance of each hyper-parameter setting was averaged over 30 random seeds. We now elaborate on the experimental setup.

Environment Models. We used an artificial neural network (ANN) to model the environment. The network input was a state s_t as well as a 1-hot encoding of an action a. The network output a vector ỹ consisting of the next or previous state ỹ_{t±1} and reward ỹ_{r±1} (± indicates we may be modelling forward or backward dynamics). The network was trained to minimise mean-squared error (MSE) between the prediction ỹ and ground-truth y, \( \frac{1}{k} \sum_{i=0}^{k} (ỹ_i - y_i)^2 \).

Value Function. We used a linear function approximator to learn Q-values. To generate state features, we used the activation of the final hidden-layer of a pre-trained DQN (Mnih et al., 2015) agent. We trained a network with 200 hidden units to convergence using the DQN algorithm and froze its weights. In each step we input state s_t to the network and extracted the hidden layer activation to form a vector of state features φ(s_t). The value function was linear in φ(s_t). We initialised weights of the linear learner using samples from \( \mathcal{N}(0, 1) \). This ensures that states have a variety of initial values, which may be optimistic or pessimistic.

Results Figure 5 shows learning curves on the three domains. As the number of steps increases so does the number planning updates. If the HVH holds, we expect algorithms that update real state values to simulated state values to show worsening performance for increasing values on the x-axis. The results support the HVH. In all domains, One-step Successor and Multi-step Successor, and Iterated One-step Predecessor struggle to learn. The planning updates performed by these algorithms harm the value function, making them perform worse than Q-learning.

The algorithms that do not update real states to simulated states — Multi-step Predecessor Dyna and Uniterated One-step Predecessor Dyna — show robust performance on all three domains. Moreover, they are also more sample efficient than Q-learning. In Cartpole for example, these algo-
6. The Impact of Model Iteration

Multi-step Predecessor and Uniterated One-step Predecessor are robust to hallucinated values. Which algorithm is preferred? Here, focus on $\beta$, a parameter controlling the length of planning rollouts. As described in Section 4, $\beta$ decays the priority of trajectories commensurate to how many times the model has been iterated to produce a given trajectory. Low values of $\beta$ aggressively decay priority and thus likely result in short rollouts while high values result in priority being primarily a function of TD error. High values of $\beta$ are beneficial as they allow for longer rollouts thereby improving sample complexity due to diversity in simulated experience (Holland et al., 2018). On the other hand, since our imperfect models are susceptible to compounding error, with sufficient iteration the model’s predictions may become poor and harmful to learning (Talvitie, 2014; 2017). Ideally, we would like to do some iteration so as to obtain the benefits of diverse planning experience without completely compromising the signal in the model’s prediction. This can be achieved by setting $\beta$ to some intermediate value greater than 0 (no iteration) but less than 1 (full iteration). As Multi-step Predecessor Dyna is the only algorithm robust to $\beta$, it likely benefits from tuning $\beta$.

Figure 3 shows Multi-step Predecessor outperforms Uniterated One-step Predecessor. Intuition for why this might be is seen in Figure 6, which shows heatmaps of $\max_{s,a} Q(s,a) \forall s \in S$ on a non-optimistically initialised agent on Borderworld. Multi-step Predecessor is much more efficient at propagating value information. Unlike Uniterated One-step Predecessor, which generates a single predecessor, updates it and then discards the trajectory, with Multi-step Predecessor we can generate trajectories radiating backwards from a particular state. Moreover, tuning $\beta$ helps even on the three benchmark domains. Figure 7 shows plots of Area Under the Curve (AUC) versus $\beta$. In these plots, Uniterated One-step Predecessor is represented by the orange line at $\beta = 0$. As can be seen, the best performance in both Catcher and Puddleworld is attained by Multi-step Predecessor with some intermediate value of $\beta$.

7. Conclusion

We presented the HVH: planning updates that move values of real states towards values of simulated states may propagate misleading, arbitrary value that impedes learning of control policies. Under controlled settings we showed evidence supporting the hypothesis — all algorithms that update real state values to simulated state values fail while those that do not perform such updates do not fail. Then, we showed that this phenomenon occurs under more realistic settings. We also introduced Multi-step Predecessor Dyna, an algorithm that allows one to gain the benefits of diverse experience offered by iterating a model without succumbing to model error. This work brings to fore a pitfall for Dyan-style planning with imperfect models. We believe highlighting this phenomenon may enable the development of Dyna algorithms that are robust to model error, including further exploration of Multi-step Predecessor Dyna variants.

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