OPTIMISTIC EXPLORATION WITH LEARNED FEATURES PROVABLY SOLVES MARKOV DECISION PROCESSES WITH NEURAL DYNAMICS

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ABSTRACT

Incorporated with the recent advances in deep learning, deep reinforcement learning (DRL) has achieved tremendous success in empirical study. However, analyzing DRL is still challenging due to the complexity of the neural network class. In this paper, we address such a challenge by analyzing the Markov decision process (MDP) with neural dynamics, which covers several existing models as special cases, including the kernelized nonlinear regulator (KNR) model and the linear MDP. We propose a novel algorithm that designs exploration incentives via learnable representations of the dynamics model by embedding the neural dynamics into a kernel space induced by the system noise. We further establish an upper bound on the sample complexity of the algorithm, which demonstrates the sample efficiency of the algorithm. We highlight that, unlike previous analyses of RL algorithms with function approximation, our bound on the sample complexity does not depend on the Eluder dimension of the neural network class, which is known to be exponentially large (Dong et al., 2021).

Keywords: Reinforcement Learning, Neural Network, Representation Learning.

1 INTRODUCTION

Reinforcement learning (RL) aims to accomplish sequential decision-making in an uncertain environment via iteratively interacting with the environment (see Sutton et al. (1998)). Equipped with modern function approximators such as deep neural networks, deep RL algorithms achieve tremendous empirical successes (Mnih et al., 2015; Silver et al., 2017; Hafner et al., 2019).

Despite its empirical successes, the theoretical understanding of deep RL is relatively underdeveloped. There are several recent works (Abbasi-Yadkori et al., 2019; Wang et al., 2019; Fan et al., 2020) that analyze RL algorithms with neural network parameterization, including policy iteration (PI) (Lagoudakis & Parr, 2003), policy gradient (PG) (Williams, 1992) and deep Q-learning (Mnih et al., 2013). However, those works depend on restrictive assumptions that either the agent has access to a simulator or the MDPs have bounded concentrability coefficients, which in fact imply that the state space is already well-explored. Another line of research (Jiang et al., 2017; Jin et al., 2020; Cai et al., 2019; Du et al., 2021) further removes such assumptions by conducting provably efficient exploration in RL. Such a direction of research typically hinges on a low-rank MDP assumption. Thus, those works either assume that the MDP is linear in the known feature or propose computational-inefficient algorithms, limiting the ability to explore the environment with neural network parameterization. To explore the environment with neural network parameterization, a recent line of work (Wang et al., 2020; Jin et al., 2021a) analyzes the use of general function approximators in RL, covering neural network parameterization as a special case. Such analyses typically depend on the Eluder dimension (Russo & Van Roy, 2013), which unfortunately can be exponentially large even for a simple neural network class (Dong et al., 2021) and thus makes the results statistically inefficient for neural network parameterization. Therefore, we raise the following question:

Can we design RL algorithms that can conduct provably efficient exploration in structured environments with neural network parameterization?

Specifically, Our goal is to **develop computational-efficient algorithms whose sample efficiency does not depend on the Eluder dimension of neural networks** for structured environments with neural network parameterization. Our key insight is that, when the transition dynamics is captured by an energy-based model, we leverage the spectral decomposition of the kernel such that the challenge of distribution shift is characterized by the effective dimension of the kernel. To illustrate this insight, we propose a new model called *MDPs with neural dynamics*, which allows neural network parameterization and captures various MDP models proposed in previous works, including the KNR model (Kakade et al., 2020) and the linear MDP model (Jin et al., 2020). We then propose an algorithm, namely, *Exploration with Learnable Neural Features* (ELNF), and show that ELNF is sample efficient. ELNF iteratively fits the transition dynamics and reward functions with neural networks. Upon fitting the models, ELNF conducts exploration based on upper confidence bounds (UCB) (Abbasi-Yadkori et al. (2011)), which are obtained from the feature maps that correspond to the fitted model. We remark that the bonus in ELNF can be efficiently computed.

Contributions. Our contribution is threefold. First, we identify a class of models that incorporates NN feature representation, which captures nonlinearity in the transition dynamics beyond the KNR and linear MDP model. We also show that our proposed setting can generalize to models in previous works (Kakade et al. (2020), Ren et al. (2021)). Second, we propose a new algorithm, namely ELNF, which tackles our proposed *MDPs with neural dynamics*. **Our algorithm is computationally efficient when we have an optimization oracle for the model estimation**. Third, we analyze the sample complexity of ELNF and show that ELNF is sample efficient. A key feature of ELNF is that **the sample complexity of ELNF depends only on the covering number of neural network classes and does not depend on the corresponding Eluder dimension.** We highlight that **our work is the first to cover arbitrary NN classes with bounded log-covering numbers.** In contrast, **previous research typically depends on the Eluder dimension (Russo & Van Roy, 2013) of the hypothesis class, which is exponentially large for simple neural network classes (Dong et al., 2021).**

1.1 Related Work

Our work is closely related to the line of research on provably efficient exploration in the function approximation setting (Jiang et al., 2017; Jin et al., 2020; Cai et al., 2019; Du et al., 2021; Uehara et al., 2021; Zhang et al., 2022a). Such a line of research typically hinges on MDPs with a low-rank structure. For instance, the study of linear MDPs (Jin et al., 2020; Cai et al., 2019) requires that the transition dynamics are linear in the known feature map. In contrast, the feature maps are unknown in our setting and need to be estimated. The study of low-rank MDPs (Jiang et al., 2017; Du et al., 2021; Uehara et al., 2021; Ren et al., 2022) is more closely aligned to our work in the sense that the feature map is unknown and needs to be estimated. Jiang et al. (2017) and Du et al. (2021) require optimistic planning over the confidence set of transition dynamics, which is computationally inefficient. Uehara et al. (2021) and Ren et al. (2022) propose an algorithm for low-rank MDP that is both computationally efficient and sample efficient. Nevertheless, they only consider finite hypothesis classes, and require sampling from the stationary distribution of the MDP.

Our work is also related to the study of provably efficient exploration with general function approximation (Wang et al., 2020; Jin et al., 2021a). Nevertheless, previous results typically depend on the Eluder dimension (Russo & Van Roy, 2013) of the hypothesis class, which is exponentially large for simple neural network classes (Dong et al., 2021). Yang et al. (2020) achieves sample-efficient exploration based on the overparameterized neural networks (Simsek et al., 2021) as the function approximator. However, their analysis hinges on the neural tangent kernel (NTK) and can not handle NNs beyond NTK regime. In contrast, our analysis can adapt to generic neural network classes.

Our work is also related to the analysis of model-based RL (Osband & Van Roy, 2014; Ayoub et al., 2020; Kakade et al., 2020) and representation learning (Ren et al., 2021; Nachum & Yang, 2021; Zhang et al., 2022b). The definition of our *MDPs with neural dynamics* generalizes that in Kakade et al. (2020) and Ren et al. (2021). In contrast to the KNR model in Kakade et al. (2020), we can handle the infinite neural network hypothesis class and do not require the nonlinear feature map to be known. Ren et al. (2021) require sampling from the posterior distribution of the hypothesis class, which is computational-inefficient when the hypothesis class is large. In addition, the sample complexity bound of Ren et al. (2021) depends on the Eluder dimension of the feature map class, which is exponentially large for simple neural network classes (Dong et al., 2021). In contrast, our sample complexity bound depends only on the neural network classes only through its capacity.

Our work is motivated by the complexity analysis of neural network classes. Dong et al. (2021) show that the Eluder dimension of one-layer neural network classes is exponentially large, suggesting that the previous analysis of RL algorithms based on the Eluder dimension (Russo & Van Roy, 2013) may not be applicable to neural networks.

1.2 Notation

For a vector $v \in \mathbb{R}^d$, we define $\|v\|_2 = (\sum_{i=1}^d v_i^2)^{1/2}$, where v_i is the i-th element of v. For a real-valued function $f : \mathcal{X} \to \mathbb{R}$, we define $\|f\|_\infty = \max_{x\in\mathcal{X}} |f(x)|$. For a vector-valued function $f : \mathcal{X} \to \mathbb{R}^d$, we define $\|f\|_{\infty,2} = \max_{x\in\mathcal{X}} \|f(x)\|_2$. For a sequence of real-valued functions $r = \{r_h\}_{h=1}^H \subset \mathcal{X} \to \mathbb{R}$, we define $\|r\|_\infty = \sup_{h\in[H],x\in\mathcal{X}} |r_h(x)|$. We denote by $\mathcal{N}(\mathcal{F}, \epsilon, \|\cdot\|)$ the ϵ-covering number of the function class $\mathcal{F}$ with respect to the norm $\|\cdot\|$, define $H_\infty(\mathcal{F}, \epsilon) = \log \mathcal{N}(\mathcal{F}, \epsilon, \|\cdot\|_\infty)$ for a real-valued function class $\mathcal{F}$, and define $H_2(\mathcal{F}, \epsilon) = \log \mathcal{N}(\mathcal{F}, \epsilon, \|\cdot\|_{\infty,2})$ for a vector-valued function class $\mathcal{F}$. We further define $[n] = \{1, \ldots, n\}$ when n is an integer. For a set $\mathcal{C}$, we denote by $\Delta(\mathcal{C})$ the set of the distributions over $\mathcal{C}$, and $\mathcal{U}(\mathcal{C})$ the uniform distribution over $\mathcal{C}$. For $g : \mathcal{X} \to \mathbb{R}$ and $\mathcal{X}_n = \{x_1, \ldots, x_n\} \subset \mathcal{X}$, we define $g[\mathcal{X}_n] = (g(x_1), \ldots, g(x_n))^\top$.

2 Preliminary

We consider an episodic MDP $\mathcal{V}^* = (\mathcal{S}, \mathcal{A}, H, \mathcal{P}^*, r^*)$ with a state space $\mathcal{S} \in \mathbb{R}^d$, an action space $\mathcal{A}$, a horizon H, transition kernels $\mathcal{P}^* = \{\mathcal{P}_h^*\}_{h=1}^H$, and reward functions $r^* = \{r_h^*\}_{h=1}^H$. We assume that the reward functions are bounded and deterministic, that is, $\|r_h^*\|_\infty \in [0, 1]$ for all $h \in [H]$. We also assume that the action space is finite, that is, $|\mathcal{A}| < \infty$. The agent iteratively interacts with the environment as follows. At the beginning of each episode, the agent determines a policy $\pi = \{\pi_h\}_{h=1}^H$, where $\pi_h : \mathcal{S} \to \Delta(\mathcal{A})$ for any $h \in [H]$. Without loss of generality, we assume that the initial state is fixed to $s_{\text{init}} \in \mathcal{S}$ across all episodes. At the h-th step, the agent receives a state s_h and takes an action a_h following $a_h \sim \pi_h(\cdot \mid s_h)$. Subsequently, the agent receives a reward $r_h^*(s_h, a_h)$ and the next state following $s_{h+1} \sim \mathcal{P}_{h+1}^*(\cdot \mid s_h, a_h)$. The episode ends after the agent receives the last state s_{H+1}. For a given policy $\pi = \{\pi_h\}_{h=1}^H$, where $\pi_h : \mathcal{S} \to \Delta(\mathcal{A})$ for any $h \in [H]$, we define the value function V_h^π and the Q-function Q_h^π for any $h \in [H]$ as

$$
\begin{aligned}
V_h^\pi(s; r^*, \mathcal{P}^*) &= \mathbb{E}_{\pi,\mathcal{P}^*}\Big[\sum_{i=h}^H r_i^*(s_i, a_i) \,\Big|\, s_h = s\Big], \\
Q_h^\pi(s, a; r^*, \mathcal{P}^*) &= \mathbb{E}_{\pi,\mathcal{P}^*}\Big[\sum_{i=h}^H r_i^*(s_i, a_i) \,\Big|\, s_h = s, a_h = a\Big].
\end{aligned} \tag{2.1}
$$

Here the expectation $\mathbb{E}_{\pi,\mathcal{P}^*}[\cdot]$ in (2.1) is taken with respect to $s_{i+1} \sim \mathcal{P}_i^*(\cdot \mid s_i, a_i)$ and $a_i \sim \pi_i(\cdot \mid s_i)$ for $i \in \{h, h+1, \ldots, H\}$. For convenience, we define $V_{H+1}^\pi(s; r, \mathcal{P}) = 0$ for any state $s \in \mathcal{S}$, reward function r, transition kernel $\mathcal{P}$ and policy π. For simplicity, we define the expected total reward $J(\pi; r^*, \mathcal{P}^*)$ as $J(\pi; r^*, \mathcal{P}^*) = V_1^\pi(s_{\text{init}}; r^*, \mathcal{P}^*)$. We have the following Bellman equations for any $(s, a, h) \in \mathcal{S} \times \mathcal{A} \times [H]$ and any policy π,

$$
\begin{aligned}
V_h^\pi(s; r^*, \mathcal{P}^*) &= \big\langle Q_h^\pi(s, \cdot\,; r^*, \mathcal{P}^*), \pi_h(\cdot \mid s)\big\rangle_{\mathcal{A}}, \\
Q_h^\pi(s, a; r^*, \mathcal{P}^*, \pi) &= \mathbb{E}_{\mathcal{P}^*}\big[r_h^*(s_h, a_h) + V_{h+1}^\pi(s_{h+1}; r^*, \mathcal{P}^*) \,\big|\, s_h = s, a_h = a\big],
\end{aligned}
$$

where $\langle \cdot, \cdot \rangle_{\mathcal{A}}$ is the inner product over $\mathbb{R}^{\mathcal{A}}$, and $\mathbb{E}_{\mathcal{P}^*}[\cdot]$ is taken with respect to $s_{h+1} \sim \mathcal{P}_h^*(\cdot \mid s_h, a_h)$. The goal of RL is to find a policy π^* that maximizes the expected total reward. Specifically, for the episodic MDP $\mathcal{V}^* = (\mathcal{S}, \mathcal{A}, H, \mathcal{P}^*, r^*)$, We define $\pi^* \in \operatorname{argmax}_\pi J(\pi; r^*, \mathcal{P}^*)$ as an optimal policy. Correspondingly, we define the optimal Q-function Q_h^* and the optimal value function V_h^* as $Q_h^*(s, a; r^*, \mathcal{P}^*) = Q_h^{\pi^*}(s, a; r^*, \mathcal{P}^*)$ and $V_h^*(s; r^*, \mathcal{P}^*) = V_h^{\pi^*}(s; r^*, \mathcal{P}^*)$ for any $(s, a) \in \mathcal{S} \times \mathcal{A}$.

3 Markov Decision Processes with Neural Dynamics

In this paper, our goal is to develop a provably efficient algorithm for RL problems adapted with large feature space, such as neural networks (NNs). To this end, we introduce the MDPs with neural dynamics, whose reward and transition dynamics are parameterized by NNs.

Motivation. Our definition is motivated by the kernelized nonlinear regulator (KNR). In a KNR model, the transition kernel takes the following form,

$$s_{h+1} = W_h^* \phi_h^*(s_h, a_h) + \epsilon, \qquad \epsilon \sim \mathcal{N}(0, I_d), \tag{3.1}$$

where ϕ_h^* is a known nonlinear feature map. Former research proposes sample-efficient algorithms for such a model. Although such a KNR setting empowers sample efficient RL (Kakade et al. (2020)), it is relatively restrictive in the following two aspects. First, the feature map ϕ_h^* and the expected reward r_h^* are known a priori. Second, the model only imposes nonlinearity on (s_h, a_h) via the known feature map, while the conditional expectation of the next state given s_h, a_h is a linear function of $\phi_h^*(s_h, a_h)$. In other words, when ϕ_h^* is known, the transition dynamics can be recovered via linear system identification methods such as ridge regression.

To generalize the KNR model, we interpret (3.1) as an energy-based model. More specifically, we can write the transition of the MDP in (3.1) as

$$\mathcal{P}_h^*(s_{h+1} \mid s_h, a_h) \propto \exp\big(-E(s_{h+1}, s_h, a_h)\big), \tag{3.2}$$

where the energy function $E(s_{h+1}, s_h, a_h)$ is defined as

$$E(s_{h+1}, s_h, a_h) = \|s_{h+1} - W_h^* \phi_h^*(s_h, a_h)\|_2^2 / 2. \tag{3.3}$$

Here (3.2) omits a normalization factor, which is a function of (s_h, a_h). We generalize this model and impose nonlinearity on the next state s_{h+1} by substituting a nonlinear feature map $\psi_{h+1}^*(s_{h+1})$ for s_{h+1} in (3.3). Such a generalization allows us to incorporate the nonlinearity of the next state in the model. In addition, we assume that the nonlinear feature maps ϕ_h^* and ψ_{h+1}^* are unknown and need to be estimated from pre-specified feature classes Φ and Ψ, which for example, can be two classes of NNs. We further assume that the expected reward r^* is unknown and needs to be estimated from the reward function class $\mathcal{R}$. We formalize our generalization in the following definition.

Definition 3.1 (MDPs with Neural Dynamics)**.** *An episodic MDP $(\mathcal{S}, \mathcal{A}, H, \mathcal{P}^*, r^*)$ is an MDP with neural dynamics if its reward function $r^* = \{r_h^*\}_{h=1}^H$ belongs to a reward function class $\mathcal{R}$, which is a known function class that consists of NNs, and the transition kernel of the MDP $\mathcal{P}^* = \{\mathcal{P}_h^*\}_{h=1}^H$ takes the following form,*

$$\mathcal{P}_h^*(s_{h+1} \mid s_h, a_h) \propto \exp\Big(-\big\|\phi_h^*(s_h, a_h) - \psi_{h+1}^*(s_{h+1})\big\|_2^2 / 2\Big). \tag{3.4}$$

Here $\phi_h^* \in \Phi : \mathbb{R}^d \times \mathcal{A} \to \mathbb{R}^m$ and $\psi_{h+1}^* \in \Psi : \mathbb{R}^d \to \mathbb{R}^m$ are two unknown feature maps, and Φ, Ψ are two known feature map classes that consist of NNs. We denote by $\mathcal{M}$ the set of all the transition kernels that take the form of (3.4), and let $\mathcal{X} \in \mathbb{R}^m$ denote the union of the image spaces of the feature maps, namely,

$$\mathcal{X} = \{h(s, a) \mid (h, s, a) \in \Phi \times \mathcal{S} \times \mathcal{A}\} \cup \{h(s) \mid (h, s) \in \Psi \times \mathcal{S}\} \subseteq \mathbb{R}^m.$$

Generality of Definition 3.1. We remark that Definition 3.1 is a significant generalization of stochastic nonlinear systems beyond KNR. For instance, when $\psi_{h+1}^*(s_{h+1}) = s_{h+1}$, the transition kernel in Definition 3.1 takes the following form,

$$\mathcal{P}_h^*(s_{h+1} \mid s_h, a_h) \propto \exp\Big(-\big\|s_{h+1} - \phi_h^*(s_h, a_h)\big\|_2^2 / 2\Big),$$

which is the transition kernel in Ren et al. (2021). Therefore, we recover the model in Ren et al. (2021) when ψ_{h+1}^* is known to be the identity map and the reward function is known. Moreover, the transition kernel defined in (3.4) also includes a class of nonlinear dynamics satisfying

$$s_{h+1} = (\psi_{h+1}^*)^{-1}\big(\phi_h^*(s_h, a_h) + \epsilon_h\big),$$

where $\mathcal{S} \subseteq \mathbb{R}^m$, $\psi_{h+1}^* \colon \mathbb{R}^m \to \mathbb{R}^m$, the determinant of the Jacobian matrix of ψ_{h+1}^* is a constant, and ϵ_h is a Gaussian noise. Our model significantly generalizes such a model by allowing a possibly noninvertible feature map ψ_{h+1}^*.

Relationship with Kernelized Linear MDP. Recall that $K(x, y) = \exp(-\|x - y\|_2^2/2)$ is also known as the Gaussian RBF kernel, which induces a reproducing kernel Hilbert space (RKHS) defined on $\mathbb{R}^m$ (Rahimi et al., 2007). (See Appendix §D for a brief introduction of RKHS.) Intuitively, $K(x, y)$ measures the proximity between x and y in the kernel space. From this perspective, the transition

kernel in (3.4) specifies the next state s_{h+1} by measuring the proximity of the representations $\phi_h^*(s_h, a_h)$ and $\psi_{h+1}^*(s_{h+1})$. Besides, since $K(x, y)$ can be written as $\langle k(x), k(y)\rangle_{\mathcal{H}}$, where the feature map of the RKHS k is defined as $k(x) = K(x, \cdot)$, and $\langle \cdot, \cdot \rangle_{\mathcal{H}}$ is the inner product of the RKHS respectively. Thus, (3.4) can be equivalently written as

$$\mathcal{P}_h^*(s_{h+1} \mid s_h, a_h) = \Big\langle Z_h^*(s_h, a_h) \cdot k\big(\phi_h^*(s_h, a_h)\big), k\big(\psi_{h+1}^*(s_{h+1})\big) \Big\rangle_{\mathcal{H}},$$

where $Z_h^*(s_h, a_h)$ is the normalization factor in (3.4). Thus, when Z_h^* is known, our model can be regarded as an RKHS extension of the linear MDP model (Jin et al., 2020). This is the case when ψ^* is the identity maps but unknown to the learner, and $Z_h^*(s_h, a_h)$ becomes a constant (Ren et al., 2021). See Appendix §D for more details of the relationship between the model in (3.4) and RKHS.

Role of NNs in Our Model. We would like to remark that the model specified in Definition 3.1 is not restricted to NNs. In fact, the definition only requires proper function classes of the reward function, representations of (s_h, a_h) and s_{h+1}, namely, $\mathcal{R}$, Φ, and Ψ. Thus, our model can also be defined for other function approximators such as polynomial spline (Unser et al., 1993), classification and regression tree (Syrgkanis & Zampetakis, 2020). Meanwhile, as we will see in the sequel, both our algorithm and the theoretical results do not hinge on NNs and can employ general function classes with bounded capacity. Here we call our model neural dynamics in order to **highlight that our work is the first one that covers arbitrary NN classes with bounded log-covering numbers**.

4 Algorithm

In this section, we introduce an algorithm for solving MDPs with neural dynamics in the online setting. We first introduce the motivation of the algorithm, and then introduce the procedure in detail.

Motivation. To strike a balance between exploration and exploitation, our algorithm follows the principle of *Optimism in the Face of Uncertainty* (Lattimore & Szepesvári, 2020). When we know the true feature maps $\{\phi_h^*\}_{h=1}^H$, we can apply kernel LSVI (Yang et al., 2020) to construct the exploration bonus since the energy-base transition admits a kernel structure. (See §3 for the details.) However, in MDPs with neural dynamics, we do not know $\{\phi_h^*\}_{h=1}^H$. A straightforward solution for handling the unknown feature maps is to learn the feature maps from the data we collect and construct the bonus based on the learned features. However, the bonus constructed by the learned features might be invalid since the learned features have errors. We handle the error in the learned feature by purposefully taking uniform actions when exploring the environment. Such a sampling scheme gives us more diverse data for model estimation. Based on this motivation, we design an iterative algorithm that outputs a policy after N iterations. In particular, in each iteration $n \in [N]$, our algorithm performs the following four steps: (i) sampling new data from the environment, (ii) estimating the model via maximum likelihood estimation, (iii) constructing exploration incentives using the features of the learned model, and (iv) updating the online policy for exploration via planning on the learned model.

Sampling Scheme. As we mentioned in §3, the transition of MDPs with neural dynamics can be written as an energy-based model and admits the Gaussian RBF kernel. To exploit the kernel structure in the transition, we explore the environment using the exploration bonus induced by the Gaussian RBF kernel and the feature maps learned from the data, which is motivated by Yang et al. (2020). However, since the bonus is not induced by the true underlying feature, it might fail to indicate the most uncertain state-action pairs for exploration. To mitigate such an issue, we combine the uniform policy, which samples action from the uniform distribution over the action space, with the optimistic policy during the sampling procedure. Intuitively, such a sampling scheme provides a wider coverage over the state-action space and better explores the environment.

To simplify the presentation of the algorithm in our work, we introduce an extended MDP, where we assign meanings to steps $h = -1, 0, H+1$, and $H+2$. In particular, the interaction of an agent with the extended MDP starts with a dummy initial state s_{-1}. During the interaction, all the dummy state and action sequences $\{s_{-1}, a_{-1}, s_0, a_0\}$ lead to the same initial state s_{init}. Moreover, the agent is allowed to interact with the environment for two steps after observing the final state s_{H+1} of an episode. Nevertheless, the agent only collects the reward $r_h(s_h, a_h)$ at steps $h \in [H]$, which leads to the same learning objective as the original MDP. In addition, we denote by $[H]^+ = [-1, 0, \ldots, H+2]$ the set of steps in the extended MDP. In the sequel, we do not distinguish between an MDP and an extended MDP for the simplicity of presentation.

Now we describe the sampling procedure in detail. In the n-th iteration of our algorithm, given the previously collected dataset $D_{h,i}^{n-1}$ for $i \in \{0,1,2\}$ and $h \in [H]$, we interact with the MDP following the policy $\pi^n = \{\pi_h^n\}_{h=-1}^H$ and obtain the new dataset $D_{h,i}^n$ for $i \in \{0,1,2\}$ and $h \in [H]$. Specifically, for any $h \in \{-1,\ldots,H\}$, we start from the initial state s_{-1} and choose the action $a_{\bar{h}} \sim \pi_{\bar{h}}^n(\cdot \mid s_{\bar{h}})$ in the $\bar{h}$-th step when $\bar{h} \in \{-1,\cdots,h\}$, and choose the action $a_{\bar{h}} \sim \mathcal{U}(\mathcal{A})$ when $\bar{h} \in \{h+1, h+2\}$. Here $\mathcal{U}(\mathcal{A})$ is the uniform distribution over the action space $\mathcal{A}$. By following such a procedure, we obtain the following trajectory,

$$s_{-1}, a_{-1}, s_0, a_0, s_1, a_1, r_1, \ldots, s_{h+2}, a_{h+2}, r_{h+2}, s_{h+3}, \tag{4.1}$$

where $s_1 = s_{\text{init}}$. Then, we label the obtained trajectory as follows,

$$s_{h+i,i}^n = s_{h+i}, \qquad a_{h+i,i}^n = a_{h+i}, \qquad r_{h+i,i}^n = r_{h+i}, \qquad \bar{s}_{h+i,i}^n = s_{h+i+1},$$

for any $i \in \{0,1,2\}$. We then update the dataset as follows,

$$\mathcal{D}_{h,i}^n = \mathcal{D}_{h,i}^{n-1} \cup \big\{(s_{h,i}^n, a_{h,i}^n, r_{h,i}^n, \bar{s}_{h+i,i}^n)\big\} = \big\{(s_{h,i}^\tau, a_{h,i}^\tau, r_{h,i}^\tau, \bar{s}_{h+i,i}^\tau)\big\}_{\tau=1}^n \tag{4.2}$$

for any $i \in \{0,1,2\}$ and $h \in [H]$. The index i in (4.2) indicates how many steps of the uniform policy we need to execute to obtain such a dataset. Intuitively, the dataset with a bigger index i has a better coverage over the state-action space $\mathcal{S} \times \mathcal{A}$. See Figure 1 for an illustration of the sampling scheme, which is summarized in Algorithm 1.

Algorithm 1 Sampling Scheme

Input: Policy $\pi^n = \{\pi_h^n\}_{h=-1}^H$, datasets $\mathcal{D}_{h,i}^{n-1}$ for $i \in \{0,1,2\}$ and $h \in [H]$.
for $h = -1, \ldots, H$ **do**
  Interact with the environment to obtain the trajectory in (4.1) by first executing π^n from s_{-1} to s_h, and then executing $\mathcal{U}(\mathcal{A})$ for two more steps. ▷ Sampling
  Set $(s_{h+i,i}^n, a_{h+i,i}^n, r_{h+i,i}^n, \bar{s}_{h+i,i}^n) \leftarrow (s_{h+i}, a_{h+i}, r_{h+i}, s_{h+i+1})$ for $i \in \{0,1,2\}$, where $(s_{h+i}, a_{h+i}, r_{h+i}, s_{h+i+1})$ is defined in (4.1).
  Set $\bar{\mathcal{D}}_{h+i,i}^n \leftarrow \big\{(s_{h+i,i}^n, a_{h+i,i}^n, r_{h+i,i}^n, \bar{s}_{h+i,i}^n)\big\}$ for $i \in \{0,1,2\}$. ▷ Labeling
end for
for $h = 1, \ldots, H$ **do** ▷ Updating the datasets
  Set $\mathcal{D}_{h,i}^n \leftarrow \mathcal{D}_{h,i}^{n-1} \cup \bar{\mathcal{D}}_{h,i}^n$ for $i \in \{0,1,2\}$.
end for
Return: Datasets $\{\mathcal{D}_{h,i}^n\}_{h=1,i=0}^{h=H,i=2}$.

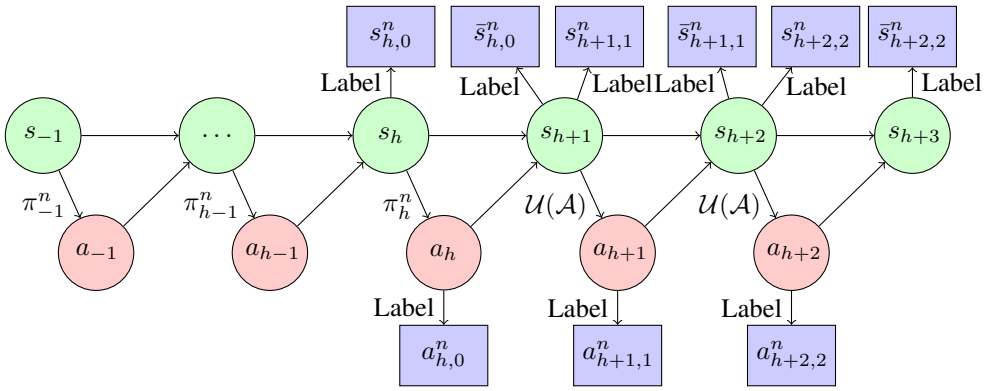

Figure 1: Sampling procedure in the h-th trajectory of the n-iteration. We first execute the optimistic policy for h steps, and then execute the uniform policy for two steps. Finally, we label the collected data as the figure shows.

Model Estimation. To estimate the model, we solve the following optimization problems,

$$\widehat{r}_h^n = \operatorname*{argmin}_{r\in\mathcal{R}} \sum_{i=1}^{2} \sum_{(s_h,a_h,r_h,s_{h+1})\in\mathcal{D}_{h,i}^n} \big[r_h - r(s_h,a_h)\big]^2, \tag{4.3}$$

$$\widehat{\mathcal{P}}_h^n = \operatorname*{argmin}_{\mathcal{P}\in\mathcal{M}} -\sum_{i=1}^{2} \sum_{(s_h,a_h,r_h,s_{h+1})\in\mathcal{D}_{h,i}^n} \log \mathcal{P}(s_{h+1} \mid s_h, a_h). \tag{4.4}$$

Here $\mathcal{R}$ and $\mathcal{M}$ are the reward function class and the transition kernel class defined in Definition 3.1. We denote by ϕ_h^n and ψ_{h+1}^n the feature maps that correspond to the transition kernel $\widehat{\mathcal{P}}_h^n$ estimated in (4.4). To simplify our analysis, we assume that there exists an oracle that returns the global minimum of the optimization problems (4.3) and (4.4). Similar assumption also arises in the previous study of RL (Fan et al., 2020; Kakade et al., 2020; Uehara et al., 2021; Jin et al., 2021a).

Remark 4.1 (Transition Estimation)**.** *We would like to remark that the method for estimating the transition is not restricted to maximum likelihood estimation (MLE). Methods including variational autoencoder (Kingma & Welling, 2013), score matching (Hyvärinen & Dayan, 2005) can also be used for transition estimation. Our sample complexity bound holds for any transition estimator whose total variance error has an upper bound.*

Exploration Bonus. The transition kernel in Definition 3.1 is closely related to the radial basis function (RBF) kernel. In the sequel, we define the bonuses for exploration and update the policy based on such bonuses. Specifically, for a fixed feature map $\phi : \mathcal{S} \to \mathbb{R}$, we define the Gram matrix $K_h^n[\phi]$ and the function $k_h^n[\phi] : \mathcal{S}\times\mathcal{A} \to \mathbb{R}^n$ as follows,

$$K_h^n[\phi] = \Big[K\big(\phi(s_{h,1}^\tau, a_{h,1}^\tau), \phi(s_{h,1}^{\tau'}, a_{h,1}^{\tau'})\big)\Big]_{\tau,\tau'=1}^n \in \mathbb{R}^{n\times n},$$

$$k_h^n[\phi](s,a) = \Big[K\big(\phi(s,a), \phi(s_{h,1}^1, a_{h,1}^1)\big), \ldots, K\big(\phi(s,a), \phi(s_{h,1}^n, a_{h,1}^n)\big)\Big]^\top \in \mathbb{R}^n,\ \forall (s,a)\in\mathcal{S}\times\mathcal{A},$$

where $\{(s_{h,1}^\tau, a_{h,1}^\tau, r_{h,1}^\tau, \bar{s}_{h,1}^\tau)\}_{\tau=1}^n \in \mathcal{D}_{h,1}^n$. We then define the bonus u_h^n as follows,

$$\begin{aligned} &u_h^n(s,a) = \min\big\{2H+2, \beta\widetilde{u}_h^n(s,a)/\lambda\big\}, \\ &\text{where} \quad \widetilde{u}_h^n(s,a) = 1 - k_h^n[\phi_h^n](s,a)^\top\big(\lambda I + K_h^n[\phi_h^n]\big)^{-1} k_h^n[\phi_h^n](s,a). \end{aligned} \tag{4.5}$$

Here $\beta > 0$ and $\lambda > 0$ are the tuning parameters. We remark that the form of the bonus in (4.5) aligns with the bonus in other previous works that use kernel functions for function approximation (Srinivas et al., 2009; Yang et al., 2020).

Remark 4.2 (Dependency of Rewards on Features.)**.** *Here we do not require that the reward depends on the feature in the transition kernel, which is different from the literature in linear MDPs (Cai et al., 2019; Jin et al., 2020). Common sense seems to dictate that we can not characterize the uncertainty using the feature without such a dependency. However, the estimation error of the reward estimators $\widehat{r}_h^n$ in the empirical measure can be bounded from the above by the property of the least square estimator. Therefore, the uncertainty of r_h^* in the distribution induced by any new policy, such as π^*, can be bounded from the above by the distribution shift, which is characterized by u_{h-1}^n. Such an observation allows us to characterize the uncertainty of the reward estimator even when the reward does not depend on the feature in the transition kernel.*

Policy Update. We update the policy π^{n+1} by setting it as the optimal policy of the learned model, which can be efficiently computed by dynamic programming. Due to the space limit, we defer the details of the planning algorithm to Appendix §B. We remark that we can also apply other model-based algorithms, including *Dyna* (Sutton, 1991) and *Gradient-Aware Model-based Policy Search* (D'Oro et al., 2020), to compute the optimal policy of the learned model.

Remark 4.3 (Computational Efficiency)**.** *Our algorithm is oracle efficient in the sense that our algorithm is computationally efficient given an optimization oracle for model estimation, which also appears in the previous study (Fan et al., 2020; Kakade et al., 2020; Uehara et al., 2021). More specifically, the bonus and the policy in each iteration can be efficiently computed by (4.5) and Algorithm 3 in the appendix. The existing literature on general function approximation requires either global optimism over the confidence set (Kakade et al., 2020; Jin et al., 2021a) or posterior sampling over the hypothesis set (Ren et al., 2021), which can not be computed efficiently.*

Algorithm 2 Exploration with Learnable Neural Features (ELNF)

1: **Input:** Failure probability $\delta > 0$, tuning parameters β, $\lambda > 0$.
2: Initialize: Set $\pi^1 = \{\pi_h^1\}_{h=-1}^H$, where $\pi_h^1(\cdot \mid s) = \mathcal{U}(\mathcal{A})$ for any $(s,h) \in \mathcal{S} \times [H]$, and set $\mathcal{D}_{h,i}^0 = \emptyset$ for all $(h,i) \in [H] \times \{0,1,2\}$.
3: **for** $n = 1, \ldots, N$ **do**
4: Set $\{\mathcal{D}_{h,i}^n\}_{h=1,i=0}^{h=H,i=2}$ by applying Algorithm 1 (Sampling Scheme) with the policy π^n and the datasets $\{\mathcal{D}_{h,i}^{n-1}\}_{h=1,i=0}^{h=H,i=2}$ as the input. ▷ Sampling
5: Set $\{\widehat{r}_h^n\}_{h=1}^H$ and $\{\widehat{\mathcal{P}}_h^n\}_{h=1}^H$ as in (4.3) and (4.4), respectively. ▷ Model estimation
6: Set $\{\phi_h^n\}_{h=1}^H$ and $\{\psi_{h+1}^n\}_{h=1}^H$ as the feature maps corresponding to $\{\widehat{\mathcal{P}}_h^n\}_{h=1}^H$.
7: Set $\{u_h^n\}_{h=1}^H$ as in (4.5). ▷ Feature estimation and bonus construction
8: Set π^{n+1} by applying Algorithm 3 (Planning Algorithm) in the appendix with the learned model $\{\widehat{r}_h^n\}_{h=1}^H$, $\{\mathcal{P}_h^n\}_{h=1}^H$, and the bonuses $\{\widehat{u}_h^n\}_{h=1}^H$ as the input. ▷ Planning
9: **end for**
10: **Return:** $\widehat{\pi} = \mathcal{U}\big(\{\pi^n\}_{n=2}^{N+1}\big)$.

5 Theory

In the sequel, we present the analysis of ELNF. We first present the boundedness assumption on the model.

Assumption 5.1 (Boundedness of Model)**.** *We assume that the state space $\mathcal{S}$ is a bounded set of $\mathbb{R}^d$, and the Lebesgue measure of $\mathcal{S}$ is an absolute constant. We also assume that $\max\{\|\phi(s,a)\|_2, \|\psi(s)\|_2\} \leq R$ for all $(s,a,\phi,\psi) \in \mathcal{S} \times \mathcal{A} \times \Phi \times \Psi$. We further assume that $0 \leq r(s,a) \leq 1$ for any $(s,a,r) \in \mathcal{S} \times \mathcal{A} \times \mathcal{R}$.*

Since $\mathcal{S}$ is bounded, Assumption 5.1 is a reasonable regularity condition on the model. Similar assumptions also arise in the previous works (Cai et al. (2019), Jin et al. (2020), Jin et al. (2021b)). Next, we introduce the following assumption, which characterizes the complexity of the NN classes.

Assumption 5.2 (Decay Rate of Covering Number)**.** *There exists constants $C_{\text{net}} > 0$ and $\gamma \geq 0$ that only depend on $(\mathcal{R}, \Phi, \Psi)$, such that*

$$H_c(\epsilon) \triangleq \max\big\{H_\infty(\mathcal{R},\epsilon), H_2(\Phi,\epsilon), H_2(\Psi,\epsilon)\big\} \leq C_{\text{net}} \cdot \big(1 + \log(1/\epsilon)\big)/\epsilon^\gamma.$$

In Assumption 5.2, γ characterizes the complexity of the NN class by quantifying the growth rate of the covering number when the covering radius ϵ decays. We remark that previous research bounds the covering number of NN classes from the above at the same scale as Assumption 5.2. For example, Schmidt-Hieber (2020) and Chen et al. (2019) show that NN classes with specific structures satisfy Assumption 5.2 with $\gamma = 0$. See Lemmas C.2 and C.5 in Appendix §C for the details.

Theorem 5.3 (Sample Complexity of ELNF)**.** *We assume that Assumption 5.2 holds with $\gamma < 1/2$, and we can obtain the exact solution to the optimization problems (4.3) and (4.4). We set the tuning parameters λ and β as*

$$\lambda = C' N^{\gamma/(1+\gamma)} m \log(48HRN/\delta),$$
$$\beta = C'' H |\mathcal{A}|^{1/2} m^{1/2} N^{3\gamma/(4+4\gamma)} \sqrt{\log(48HRN/\delta)}$$

in ELNF, where m is the dimension of the image of the feature maps, C', C'' are constants that only depend on the regularity parameters in Assumption 5.1. Under Assumption 5.1 and 5.2, for the policy $\widehat{\pi}$ returned by ELNF, it holds with probability at least $1-\delta$ that

$$J(\pi^*; r^*, \mathcal{P}^*) - J(\widehat{\pi}; r^*, \mathcal{P}^*) \leq C H^5 \cdot |\mathcal{A}|^2 \cdot \xi \cdot N^{(2\gamma-1)/(2+2\gamma)} (\log N)^{m+1}.$$

Here C is a constant that only depends on the dimension m, the bound of the feature maps R, and C_{net} in Assumption 5.2, and $\xi = (\log(48HRN/\delta))^{5/2}$ is a logarithmic factor.

Proof. See Appendix §E for a detailed proof. □

In Theorem 5.3, λ is the regularization parameter that trades off between bias and variance, and β is the uncertainty coefficient, which scales with γ and N. We remark that our analysis is not restricted to NN classes, and can be extended to other bounded function classes with bounded covering numbers. We further remark that m in Theorem 5.3 is the dimension of the image of the feature maps, which can be much smaller than the dimension of the state.

Removing Dependency on Eluder Dimension. The existing literature on RL using general function approximators relies on the Eluder dimension when bounding the regret or the suboptimality (Wang et al., 2020; Jin et al., 2021a; Ren et al., 2021), which is exponentially large for a simple neural network class (Dong et al., 2021). However, we can remove such dependency in MDPs with neural dynamics. Our key insight is that we can regard MDPs with neural dynamics as kernel MDPs (Yang et al., 2020) whose feature is the composite map of the neural network and the feature map of the RKHS since the energy-base transition admits a kernel structure, which is shown in §3. Therefore, we can characterize the effect of the distribution shifts by the bonus defined by the true feature, whose sum is bounded by the effective dimension of the RKHS instead of the Eluder dimension of the NN class, without knowing the true feature. We remark that we purposefully take uniform actions when exploring the environment to obtain a valid uncertainty quantification without knowing the true feature, and $|\mathcal{A}|^2$ in the suboptimality bound is the price paid for the uniform sampling.

Moreover, in Appendix §E, we show that the suboptimality bound in Theorem 5.3 reduces to $\widetilde{\mathcal{O}}(d_{\text{eff}} N^{(2\gamma-1)/(2+2\gamma)})$ in terms of N, where d_{eff} is the effective dimension in Definition E.4 in the appendix. Such a bound connects the sample efficiency of `ELNF` to the effective dimension of the RKHS and the covering number of NN classes. Our analysis can be extended to dynamics that can be embedded in other kernel spaces, which is left as future research. We further remark that when $\gamma = 0$ in Theorem 5.3, the suboptimality bound is sublinear in N, which aligns with the previous theoretical research. We compare our work with Dong et al. (2021), Ren et al. (2021), and Yang et al. (2020) in detail as follows. Due to the space limit, we defer the detailed comparison with other related work to Appendix §A.

Comparison with Dong et al. (2021). The sample complexity is $\widetilde{\mathcal{O}}(\epsilon^{-2})$ in terms of N when the logarithmic factors are omitted and $\epsilon = 0$. Meanwhile, Theorem 5.1 in Dong et al. (2021) shows that the minimax sample complexity of solving a nonlinear bandit problem with one-layer NNs and ReLU activation is $\Omega(\epsilon^{-(d-2)})$. To obtain such a lower bound, Dong et al. (2021) assume that the action space is the unit sphere $\mathbb{S}^{d-1}$ in $\mathbb{R}^d$, which is an infinite set, while the action space in our setting is finite. In the case where $H = 1$, our model reduces to a finite-arm bandit problem whose reward is parameterized by an NN. Although the Eluder dimension of the NN class is large, the agent only needs to explore the arms of the bandits in our model, while the agent needs to explore the unit sphere in their model. Therefore, their model does not belong to our model, our result does not contradict the lower bound in Dong et al. (2021), and the sample complexity in our model is dominated by the number of arms instead of the Eluder dimension of the NN class when $H = 1$.

Comparison with Ren et al. (2021). Ren et al. (2021) studies a nonlinear model with Gaussian noise. They show that the expectation of the regret of their algorithm is

$$\widetilde{\mathcal{O}}\Big(\sqrt{H^2 N \cdot \log \mathcal{N}(\Phi, N^{-1/2}, \|\cdot\|_2) \cdot \dim_E(\Phi, N^{-1/2})}\Big),$$

where $\dim_E(\Phi, \cdot)$ is the Eluder dimension of Φ. We show in §3 that the model in Ren et al. (2021) is a special case of our model. Our bound on the suboptimality aligns with their result in terms of the number of iterations N when $\gamma = 0$. However, they do not fully exploit the kernel structure in the transition in their analysis, and their result depends on the Eluder dimension of Ψ. Lemma C.6 in Appendix §C.2 provides an example of an NN class whose ϵ-Eluder dimension is at least $\Omega(\epsilon^{-(d-1)})$ and the ϵ-log covering number is at most $\mathcal{O}(\log(1/\epsilon))$. Lemma C.6 shows that removing the dependency of the sample complexity on the Eluder dimension significantly improves the sample complexity. In addition, their algorithm requires sampling from the posterior distribution of the hypothesis class, which is difficult to implement in practice. In contrast, our algorithm only requires planning with respect to the learned model, which can be computed efficiently.

Comparison with Yang et al. (2020). Yang et al. (2020) use overparameterized NNs for function approximation in the algorithm Neural Optimistic Least-Squares Value Iteration (`NOVI`) and shows that `NOVI` is sample efficient. However, their analysis relies on the connection between overparameterized NNs and neural tangent kernel and can not handle NNs beyond NTK regime.

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