ON THE GEOMETRY OF REINFORCEMENT LEARNING IN CONTINUOUS STATE AND ACTION SPACES

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ABSTRACT

Advances in reinforcement learning have led to its successful application in complex tasks with continuous state and action spaces. Despite these advances in practice, most theoretical work pertains to finite state and action spaces. We propose building a theoretical understanding of continuous state and action spaces by employing a geometric lens. Central to our work is the idea that the transition dynamics induce a low dimensional manifold of reachable states embedded in the high-dimensional nominal state space. We prove that, under certain conditions, the dimensionality of this manifold is at most the dimensionality of the action space plus one. This is the first result of its kind, linking the geometry of the state space to the dimensionality of the action space. We empirically corroborate this upper bound for four MuJoCo environments. We further demonstrate the applicability of our result by learning a policy in this low dimensional representation. To do so we introduce an algorithm that learns a mapping to a low dimensional representation, as a narrow hidden layer of a deep neural network, in tandem with the policy using DDPG. Our experiments show that a policy learnt this way perform on par or better for four MuJoCo control suite tasks.

1 INTRODUCTION

The goal of a reinforcement learning (RL) agent is to learn an optimal policy that maximises the return which is the time discounted cumulative reward (Sutton & Barto, 1998). Recent advances in RL research have lead to agents successfully learning in environments with enormous state spaces, such as games (Mnih et al., 2015; Silver et al., 2016), and robotic control in simulation (Lillicrap et al., 2016; Schulman et al., 2015; 2017) and real environments (Levine et al., 2016; Zhu et al., 2020; Deisenroth & Rasmussen, 2011). However, we do not have an understanding of the intrinsic complexity of these seemingly large problems. For example, in most popular deep RL algorithms for continuous control, the agent's policy is parameterised by a a deep neural network (DNN) (Lillicrap et al., 2016; Schulman et al., 2015; 2017) but we do not have theoretical models to guide the design of DNN architecture required to efficiently learn an optimal policy for various environments. There have been approaches to measure the difficulty of an RL environment from a sample complexity perspective (Antos et al., 2007; Munos & Szepesvari, 2008; Bastani, 2020) but these models fall short of providing recommendations for the policy and value function complexity required to learn an optimal policy.

We view the complexity of RL environments through a geometric lens. We build on the intuition behind the *manifold hypothesis*, which states that most high-dimensional real-world datasets actually lie on low-dimensional manifolds (Tenenbaum, 1997; Carlsson et al., 2007; Fefferman et al., 2013; Bronstein et al., 2021); for example, the set of natural images are a very small, smoothly-varying subset of all possible value assignments for the pixels. A promising geometric approach is to model the data as a low-dimensional structure—a *manifold*—embedded in a high-dimensional ambient space. In supervised learning, especially deep learning theory, researchers have shown that the approximation error depends strongly on the dimensionality of the manifold (Shaham et al., 2015; Pai et al., 2019; Chen et al., 2019; Cloninger & Klock, 2020), thereby connecting the complexity of the underlying structure of the dataset to the complexity of the DNN.

As in supervised learning, researchers have applied the manifold hypothesis in RL—i.e. hypothesized that the effective state space lies on a low dimensional manifold (Mahadevan, 2005; Machado et al.,

2017; 2018; Banijamali et al., 2018; Wu et al., 2019; Liu et al., 2021). Despite its fruitful applications, this assumption—of a low-dimensional underlying structure—has never been theoretically and empirically validated in any RL setting.

Our main result provides a general proof of this hypothesis for *all* continuous state and action RL environments by proving that the effective state space is a manifold and upper bound its dimensionality by, simply, the dimensionality of the action space plus one. Although our theoretical results are for deterministic environments with continuous states and actions, we empirically corroborate this upper bound on four MuJoCo environments (Todorov et al., 2012), with sensor inputs, by applying the dimensionality estimation algorithm by Facco et al. (2017). Our empirical results suggest that in many instances the bound on the dimensionality of the effective state manifold is tight. To show the applicability and relevance of our theoretical result we empirically demonstrate that a policy can be learned using this low-dimensional representation that performs as well as or better than a policy learnt using the higher dimensional representation. We present an algorithm that does two things simultaneously: **1)** learns a mapping to a low dimensional representation, called the *co-ordinate chart*, parameterised by a DNN, and **2)** uses this low-dimensional mapping to learn the policy. Our algorithm extends DDPG (Lillicrap et al., 2016) and uses it as a baseline with a higher-dimensional representation as the input. We empirically show a surprising new DNN architecture with a bottleneck hidden layer of width equal to dimensionality of action space plus one performs on par or better than the wide architecture used by Lillicrap et al. (2016). These results demonstrate that our theoretical results, which speaks to the underlying geometry of the problem, can be applied to learn a low dimensional or compressed representation for learning in a data efficient manner. Moreover, we connect DNN architectures to effectively learning a policy based on the underlying geometry of the environment.

2 Background and Mathematical Preliminaries

We first describe the continuous time RL model and Markov decision process (MDP). This forms the foundation upon which our theoretical result is based. Then we provide mathematical background on various ideas from the theory of manifolds that we employ in our proofs and empirical results.

2.1 Continuous-Time Reinforcement Learning

We analyze the setting of continuous-time reinforcement learning in a deterministic *Markov decision process* (MDP) which is defined by the tuple $\mathcal{M} = (\mathcal{S}, \mathcal{A}, f, f_r, s_0, \lambda)$ over time $t \in [0, T)$. $\mathcal{S} \subset \mathbb{R}^{d_s}$ is the set of all possible states of the environment. $\mathcal{A} \subset \mathbb{R}^{d_a}$ is the rectangular set of actions available to the agent. $f : \mathcal{S} \times \mathcal{A} \times \mathbb{R}^+ \to \mathcal{S}$ and $f \in C^\infty$ is a *smooth* function that determines the state transitions: $s' = f(s, a, \tau)$ is the state the agent transitions to when it takes the action a at state s for the time period τ. Note that $f(s, a, 0) = s$, meaning that the agent's state remains unchanged if an action is applied for a duration of $\tau = 0$. The reward obtained for reaching state s is $f_r(s)$, determined by the reward function $f_r : \mathcal{S} \to \mathbb{R}$. s_t denotes the state the agent is at time t and a_t is the action it takes at time t. s_0 is the fixed initial state of the agent at $t = 0$, and the MDP terminates at $t = T$. The agent does not have access to the functions f and f_r, and can only observe states and rewards at a given time $t \in [0, T)$.

The agent is equipped with a policy, $\pi : \mathcal{S} \to \mathcal{A}$, that determines its decision making process. We denote the set of all the possible policies by Π. Simply put, the agent takes action $\pi(s)$ at state s. The goal of the agent is to maximise the discounted return $J(\pi) = \int_0^T e^{-\frac{l}{\lambda}} f_r(s_l) dl$, where $s_{t+\epsilon} = f(s_t, \pi(s_t), \epsilon)$ for infinitesimally small ϵ and all $t \in [0, T)$. We define the *action tangent mapping*, $g : \mathcal{S} \times \mathcal{A} \to \mathbb{R}^{d_s}$, for an MDP as

$$g(s, a) = \lim_{\epsilon \to 0^+} \frac{f(s, a, \epsilon) - s}{\epsilon} = \frac{\partial f(s, a, \epsilon)}{\partial \epsilon}.$$

Intuitively, this captures the direction in which the agents state changes at state s upon taking an action a. For notational convenience we will denote $g(s, \pi(s))$ as $g_\pi : \mathcal{S} \to \mathbb{R}^{d_s}$ and name it the *action flow* of the environment defined for a policy π. Note that g_π is a well defined function. Intuitively, g_π is the direction of change in the agent's state upon following a policy π at state s for an infinitesimally

small time. This solution is also unique (Wiggins, 1989) and can be written in the integral form as

$$s_t^\pi = s_0 + \int_0^t g_\pi(s_l^\pi) dl. \tag{1}$$

The above curve is a smooth curve if the policy is also smooth. Therefore, given an MDP, $\mathcal{M}$, and a smooth deterministic policy, $\pi \in \Pi$, the agent traverses a continuous time trajectory or curve $H_{\mathcal{M},\pi} : [0, T) \to \mathcal{S}$.

We also define the value function at time t for a policy π as the cumulative future reward starting at time t.

$$v^\pi(s_t) = \int_t^T e^{-\frac{l-t}{\lambda}} f_r(s_l) dl. \tag{2}$$

Note that the objective function, $J(\pi)$, is the same as $v^\pi(s_0)$. Our specification is very similar to classical control and continuous time RL (Cybenko, 1989; Doya, 2000) with the key difference being how we define the transition function, f.

2.2 Manifolds

MDPs, in practice, have a low-dimensional underlying structure resulting in them having fewer degrees of freedom than their nominal dimensionality. In the Cheetah MujoCo environment, with image observations, the goal of the RL agent is to learn a policy to make the Cheetah move forward as fast as possible, where the Cheetah is constrained to a plane. The actions available to the agent are providing torques at each one of the 6 joints. In the case of learning from visual input in a MuJoCo environment like 2D cheetah, one can describe the cheetah's state by its "pose" and position instead of the 128×128 pixels of the image. The idea of a low dimensional manifold embedded in a high dimensional state space formalises this.

A function $h : X \to Y$, from one open subset $X \subset \mathbb{R}^{l_1}$, to another open subset $Y \subset R^{l_2}$, is a diffeomorphism if h is bijective, and both h and h^{-1} are differentiable. Intuitively, a low dimensional surface embedded in a high dimensional Euclidean space can be parameterised by a differentiable mapping, and if this mapping is bijective we term it a diffeomorphism. Here X is said to be diffeomorphic to Y. A manifold is defined as follows.

Definition 2.1. *A subset $M \subset \mathbb{R}^k$ is called a smooth m-dimensional submanifold of $\mathbb{R}^k$ (or m-manifold in $\mathbb{R}^k$) iff every point $p \in M$ has an open neighborhood $U \subset \mathbb{R}^k$ such that $U \cap M$ is diffeomorphic to an open subset $O \subset \mathbb{R}^m$. A diffeomorphism, $\phi : U \cap M \to O$ is called a coordinate chart of M and the inverse, $\psi := \phi^{-1} : O \to U \cap M$ is called a smooth parameterisation of $U \cap M$.*

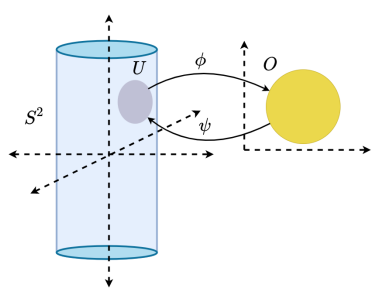


Figure 1: The surface of an open cylinder of unit radius, denoted by S^2, in $\mathbb{R}^3$ is a 2D manifold embedded in a 3D space. More formally, $S^2 = \{(x, y, z) | x^2 + y^2 = 1, z \in (-h, h)\}$ where the cylinder's height is $2h$. One can smoothly parameterise S^2 as $\psi(\theta, b) = (\sin\theta, \cos\theta, b)$. The coordinate chart is $\phi(x, y, z) = (\sin^{-1} x, z)$.

We illustrate this with an example in Figure 1. If $M \subset \mathbb{R}^k$ is a non-empty smooth m-manifold then $m \leq k$, reflecting the idea that a manifold is of lower or equal dimension than its ambient space. A smooth curve $\gamma : I \to M$ is defined from an interval $I \subset \mathbb{R}$ to the manifold M as a function that is

infinitely differentiable for all t. The derivative of γ at t is denoted as $\dot{\gamma}(t)$. The length of a curve $\gamma : I \to M$ is defined as $L(\gamma) = \int_I ||\dot{\gamma}(t)||dt$, where $|| \cdot ||$ denotes the vector norm. In the Euclidean space the distance between two points is the length of the unique straight line connecting them. Similarly, the *geodesic distance* between two points $a, b \in M$ is defined as the length of the shortest such curve, $\gamma : [0, 1] \to M$, such that $\gamma(0) = a$ and $\gamma(1) = b$. We denote the geodesic distance between $a, b \in M$ on the manifold M is denoted by the function $d_M(a, b)$. The set of derivatives of the curve at time t, $\dot{\gamma}(t)$, for all possible smooth γ, form a set that is called the tangent space. The tangent space characterises the geometry of the manifold and it is defined as follows.

Definition 2.2. *Let M be an m-manifold in $\mathbb{R}^k$ and $p \in M$ be a fixed point. A vector $v \in \mathbb{R}^k$ is called a tangent vector of M at p if there exists a smooth curve $\gamma : I \to M$ such that $\gamma(0) = p, \dot{\gamma}(0) = v$. The set*

$$T_pM := \{\dot{\gamma}(0)|\gamma : \mathbb{R} \to M \text{ is smooth}, \gamma(0) = p\}$$

of tangent vectors of M at p is called the tangent space of M at p.

Continuing our example, the tangent space of a point p in S^2 is the vertical plane tangent to the cylinder at that point. For a small enough ϵ and a vector $v \in T_pS^2$ there exists a unique curve $\gamma : [-\epsilon, \epsilon] \to S^2$ such that $\gamma(0) = p$ and $\dot{\gamma}(0) = v$.

3 State Space Geometry

The state space is typically thought of as a dense space in which all states lie, but it is not necessarily the case that all such states are reachable by the agent. Indeed, in examples such as the Cheetah environment 128x128 state space will never be observed because they do not correspond to any image of a robotic Cheetah, or even any recognizable image at all. Instead, the agent must be traversing through a much smaller subset of this space as it interacts with the world. Our goal is to characterize the geometry of this space. Two main factors constrain the states available to an agent: **1)** the transition function and the actions that are available to an agent, and **2)** the start state s_0. We therefore define $\mathcal{S}_e$ as the *effective set of states*. Under the assumptions that Π is the set of all smooth policies, $\pi : \mathcal{S} \to \mathcal{A}$, for a continuous time MDP, $\mathcal{M}$, and those made in section 2.1 we define the effective set of states as follows.

Definition 3.1. *For an MDP, $\mathcal{M}$, the effective set of states, $\mathcal{S}_e$, is defined as the union of the sets of states of all possible continuous curves traversed by the agent for the set of all smooth policies. Formally, $\mathcal{S}_e = \cup_{\pi \in \Pi}\{s|s = H_{M,\pi}(t)$ for some $t \in (0, T)\}$, where Π is the set of everywhere smooth policies in $\mathcal{S}$.*

We make three additional assumptions:

1. **Full rank Jacobian:** f has a full rank Jacobian for all $s \in \mathcal{S}, a \in \mathcal{A}$ and $t \in (0, T)$, and for a fixed policy π the solution for the equation $s_t^\pi = s$, if it exists, is unique in t.
2. **No orbits:** there exists an $\tau > 0$ such that for all $t < \tau$ and a fixed policy π the solution for the equation $s_t^\pi = s$, if it exists, is unique in t.
3. **Action space restriction condition:** There exists an $r > 0$ and an open restriction $\mathcal{A}'_s$ of $\mathcal{A}$, for every state $s \in \mathcal{S}_e$, such that $\mathcal{A}'_s \subset \mathcal{A}$ such that for all $0 < \epsilon < r$, if we have $f(s, a_1, \epsilon) = f(s, a_2, \epsilon)$ for some fixed $a_1, a_2 \in \mathcal{A}'$ then $a_1 = a_2$.

We provide further information on these assumptions and how they restrict our study in Appendix A. Under these two assumptions for the setting of continuous RL as in Section 2.1 we have the result stated below.

Theorem 3.2. *The set of effective states, $\mathcal{S}_e$, is a smooth manifold of dimensionality at most $d_a + 1$.*

We provide the proof in Appendix B. Intuitively, the action set limits the directions in which the agent can go. For example, a single action executed for a finite time interval makes the agent traverse a 1D curve. The union of all such curves is the only subset of the state space the agent can reach. The key technical idea is to construct a coordinate chart, and therefore a diffeomorphism, from a subset of low dimensional euclidean space to a subset of the state space. We fix a state s and consider the function $\phi : \mathcal{A} \times (0, r) \to \mathcal{S}$ such that $\phi(a, \epsilon) = f(s, a, \epsilon)$. This result pertains to the *global geometry* of the state manifold, meaning the state manifold everywhere has this low dimensional structure.

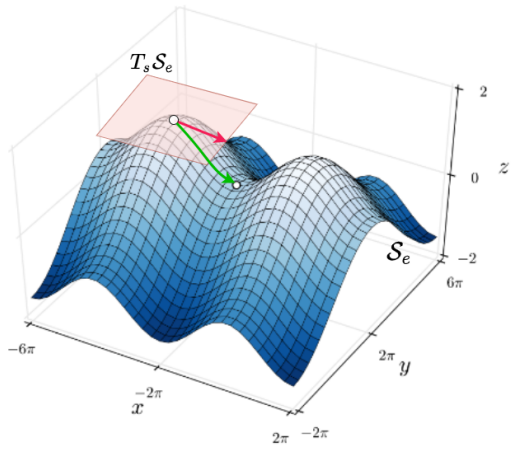


Figure 2: Consider a hypothetical scenario as in the image above where upon taking an action even though the agent moves locally at state s in the direction of the red arrow (along $g_\pi(s)$) as time progresses it ends up travelling along the green arrow which is on the manifold $\mathcal{S}_e$. There is some constraint that restricts the state space "available" to an agent. Thus, the agent can only reach the states that have a valid solution for the Equation 1 for any smooth policy.

Our result formalises the long-held idea that there is in fact a lower dimensional structure to the state manifold; in particular, this is true when $d_a + 1 < d_s$, which is almost always the case for RL environments. It also formalises the idea that the agent can only observe data for states reachable by interacting with the environment using the set of actions at its disposal. Henceforth, we refer to $\mathcal{S}_e$ as the state manifold. We also present an immediate corollary of Theorem 3.2.

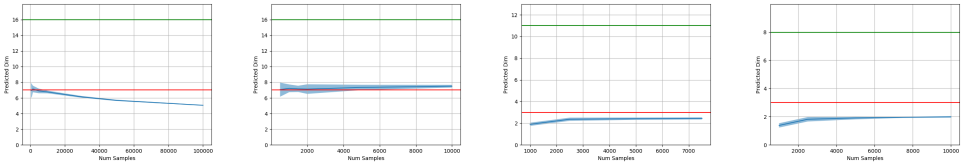
Corollary 3.3. *For every $a \in \mathcal{A}$ and fixed $s \in \mathcal{S}_e$, the action tangent mapping, $g(s, a)$, maps from the set of actions $\mathcal{A}$ to $T_s\mathcal{S}_e$ and therefore there exists a vector $v_a \in T_s\mathcal{S}_e$ such that $v_a = g(s, a)$ for all $a \in \mathcal{A}$.*

This implies that locally an agent is moving along a tangent in the tangent space of a state in the state manifold as it acts upon the environment. The corollary follows from Definition 2.2, and its proof is in Appendix B. Intuitively, Corollary 3.3 implies that locally the agent's state changes in a constrained manner dictated by the actions available to it and the *local geometry* of the manifold, i.e., the tangent space and its projection onto the state manifold. We illustrate this in Figure 2. We note that the idea of actions mapping to the tangent space was assumed earlier by Liu et al. (2021) for constrained RL but Corollary 3.3 both proves this assumption and shows that it holds in general for continuous RL environments.

4 Connections Between Continuous Time Deterministic RL and Empirical RL

We have presented our results in the continuous time RL setting, which is an underutilized theoretical tool, in the study of RL. Here, and in the experimental section, we argue that it is in fact a useful model for theoretical analysis in the continuous state and action, *discrete* time, setting. The primary intuition is that, in the context of simulated robotic control problems, our work approximates the agents behavior during the transition period $(t, t+1)$ as the action a_t changes to a_{t+1} in a smooth manner and similarly for s_t to s_{t+1}. In this context, the discrete-time observations can be viewed as time-uniform samples from an underlying continuous process.

More formally, if we consider a discrete time MDP with continuous state and action spaces, a discrete state trajectory is the sequence of states $\{s_t\}_{t=1}^T$ and similarly for actions, $\{a_t\}_{t=1}^T$. We augment the discrete time action trajectories with a function for the transition period $\vartheta : \mathcal{A} \times [0, 1] \times \mathcal{A} \to \mathcal{A}$ we can construct a model for these smooth transitions of the action. This function ϑ is such that $\vartheta(a_t, l, a_{t+1}) = a_{t+l}$ for $l \in [0, 1], \forall t \in \{0, 1, ..., T-1\}$, the boundary conditions hold, i.e., $\vartheta(a_t, 0, a_{t+1}) = a_t$ and $\vartheta(a_t, 1, a_{t+1}) = a_{t+1}$, and it is smooth in the transition time l. Note that we



(a) Walker2D (b) Cheetah (c) Reacher (d) Swimmer

Figure 3: Estimated state manifold dimensionality, in blue, is close to $d_a + 1$ (horizontal red line) and far below d_s (horizontal green line) for various environments estimated using the algorithm by Facco et al. (2017).

can also construct this ϑ such that it is differentiable at a_t for $\vartheta(a_{t-1}, l, a_t)$ and $\vartheta(a_t, 1-l, a_{t+1})$ as $l \to 1^-$. More importantly, by extending continuous time results to discrete time results we implicitly assume that there exists a function f that preserves smoothness of the state transitions. Specifically, given $a_{t+l} = \vartheta(a_t, l, a_{t+1})$ there exists a transition function f and, consequently, the action tangent mapping g, as defined in Section 2, such that $s_t + \int_0^1 g(s_t, \vartheta(a_t, l, a_{t+1}))dl$ equals s_{t+1}. The proof of existence of such a function, ϑ, is beyond the scope of our current work. Such an augmentation transforms all trajectories on this discrete time MDP to continuous time smooth curves. As in many other fields of engineering, we argue that we can only obtain measurements for various signals at discrete intervals. For example, in a robot with various joints we can only measure the joints over intervals which are then attributed to discrete time measurements. Similarly, we can actuate the motors up to a frequency and those can be considered as discrete control signals, even though the underlying physical process is continuous time.

Finally, we address the assumption of deterministic transitions. One way to model transitions is to assume that the underlying state transitions are deterministic but the observations the agent receives have additive noise. More formally, a simplistic way to model stochastic transition $F(s, a, \epsilon) = f(s, a, \epsilon) + \mathcal{N}(0, \sigma)$ is the stochastic transition function such that there is additive noise to this deterministic transition. We postulate that the effective set of states can be modeled as a manifold with each observation the agent makes lying at a certain distance to the state manifold and the distance is normally distributed. This is also the idea behind many manifold learning paradigms: the data lies at a certain distance to a manifold and this distance is distributed according to some probability law (Fefferman et al., 2013; Pai et al., 2019).

5 Empirical Validation

5.1 Empirical Dimensionality Estimation

To empirically corroborate our main result (Theorem 3.2) we perform experiments in the MuJoCo domains provided in the OpenAI Gym (Brockman et al., 2016). These are all continuous state and action spaces with $d_a < d_s$ for simulated robotic control tasks. The states are typically sensor measurements such as angles, velocities or orientation, and the actions are torques provided at various joints. We estimate the dimensionality of the state manifold $\mathcal{S}_e$. To sample data from the manifold, we record the trajectories from multiple evaluation runs of DDPG across different seeds (Lillicrap et al., 2016), with two changes: we use GELU activation (Hendrycks & Gimpel, 2016) instead of ReLU, in both policy and value networks, and also use a single hidden layer network of width 400 instead of 2 hidden layers for both the networks. This is inline with the assumptions for Theorem 3.2 in Section 3, that the policy is smooth. Performance is comparable to the original DDPG setting (see the Appendix E). For background on DDPG refer to Appendix D. We then randomly sample states from the evaluation trajectories to obtain a subsample of states, $\mathcal{D} = \{s_i\}_{i=1}^n \subset \mathcal{S}_e$.

We employ the dimensionality estimation algorithm introduced by Facco et al. (2017), which estimates the intrinsic dimension of datasets characterized by non-uniform density and curvature, to empirically corroborate Theorem 3.2. Further details about the dimensionality estimation procedure are presented in Appendix C. The results of this algorithm for four MuJoCo environments are shown in Figure 3. For all environments the estimate remains in the neighbourhood of $d_a + 1$; this is also seen in Figure

4 by Facco et al. (2017) for the Isomap faces dataset. We attribute the slight overestimate in Cheetah to noise in the observations as is common in all implementations of the environments (Brockman et al., 2016).

5.2 Learning via the Low-dimensional Manifold Representation

We now validate the relevance of Theorem 3.2 using a popular policy gradient method, deep deterministic policy gradient (DDPG) Lillicrap et al. (2016), which is discrete time. DDPG is a framework for learning in environments with continuous action spaces, and the policy and value function are parameterised by DNNs. Let θ^π be the parameters of the policy DNN. The agent learns by updating the policy parameters with respect to the discrete time discounted return, $J(\theta^\pi)$:

$$\theta^\pi \leftarrow \theta^\pi + \alpha_\pi \nabla_{\theta^\pi} J(\theta^\pi),$$

where α_π is the learning rate for the policy and $J(\theta^\pi)$ is the discounted return objective. For further details and background on DDPG please see Appendix D. We do so by learning mapping to a low dimensional manifold of size $d_a + 1$ from the control input space that feeds into the policy. The central idea is to show that this compressed representation can be used to learn a control policy with RL without any loss—and possibly even a gain— of performance.

Our goal in validating the applicability of this low dimensional representation is to learn an *isometric* coordinate chart from the high dimensional representation for states in $\mathcal{S}_e$ to a low dimensional Euclidean space $\mathbb{R}^m$, where $m \leq d_a + 1$ as noted in Theorem **??**, and then compare learning a policy using this compression of the state to learning from the full state. We denote the coordinate chart by $\psi : \mathcal{S}_e \to \mathbb{R}^{d_a+1}$ parameterised by θ^ψ. For a coordinate chart to be isometric it must preserve the geodesic distance on the manifold $\mathcal{S}_e$, meaning for $s_1, s_2 \in \mathcal{S}_e$ we have that $d_{\mathcal{S}_e}(s_1, s_2) = ||\psi(s_1; \theta^\psi) - \psi(s_2 \theta^\psi)||_2$, where $d_{\mathcal{S}_e}(s_1, s_2)$ is the geodesic distance between s_1 and s_2 on the manifold $\mathcal{S}_e$ and $|| \cdot ||_2$ denotes the Euclidean norm. Note that imposing isometry on a coordinate chart is a stronger condition than it being a diffeomorphism because it is distance preserving, in addition to being a bijection and differentiable. Such isometric mappings have been used in the past to learn the underlying manifold for high-dimensional data (Tenenbaum et al., 2000; Basri & Jacobs, 2017; Pai et al., 2019). This is done to ensure tractability of the objective that we introduce below. Given a dataset of states $\mathcal{D} = \{s_i\}_{i=1}^N \subset \mathcal{S}_e$ we propose to learn these parameters by minimizing the loss

$$L_\psi(\theta^\psi) = \frac{1}{N} \sum_{s_i, s_j \in \mathcal{D}} \left(d_{\mathcal{S}_e}(s_1, s_2) - ||\psi(s_1; \theta^\psi) - \psi(s_2 \theta^\psi)||_2 \right)^2, \tag{3}$$

which is similar to the loss for learning low-dimensional manifold embeddings introduced by Tenenbaum et al. (2000). The computation and estimation of the geodesic distance, $d_{\mathcal{S}_e}$, is particularly challenging. One approach is to use a graph, as a discrete approximation of a manifold, to calculate this geodesic distance (Yan et al., 2007; Dong et al., 2011). The graph is constructed with each datapoint as a node and an edge in between two datapoint if one of them is k_{nn}-nearest neighbor of the other in the dataset. In addition to that there is a distance attribute associated with every edge that is the Euclidean distance between the two points. Therefore, the geodesic distance between two datapoints can be approximated the sum of these edge-wise attributes for the edges constituting the shortest path between the two points. Another practical challenge in the empirical estimation of the loss L_ψ is sampling pairs of states for which we can obtain approximate geodesic distances with reasonable compute time. These two processes, estimating geodesic distance and sampling of states, are interleaved and influence the learned representation. The exact procedure employed by us is detailed in Appendix F and illustrated in Figure 8.

Although there has been significant work in learning isometric mappings (Pai et al., 2019; Basri & Jacobs, 2017) and embeddings (Tenenbaum et al., 2000; Zha & Zhang, 2003), for data sampled from a manifold, these prior works assume that the data distribution remains static throughout the training process. However, the state distribution changes with the policy in RL and this mapping feeds into the policy itself, effecting the agents performance. We learn this isometric mapping, ψ, in tandem with the policy to account for the distribution shift. To do so we introduce an intermediate hidden layer of size $d_a + 1$ in the policy DNN. The output of this layer is then trained by performing gradient descent on the loss L_ψ. In this architecture $\theta^\psi \subset \theta^\pi$ and the gradient is as follows:

$$\theta^\pi \leftarrow \theta^\pi + \alpha_\pi \nabla_{\theta^\pi} J(\theta^\pi) - \alpha_\psi \nabla_{\theta^\pi} L_\psi \theta^\psi, \tag{4}$$

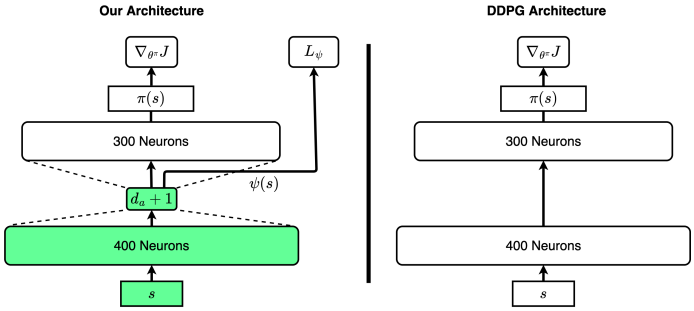
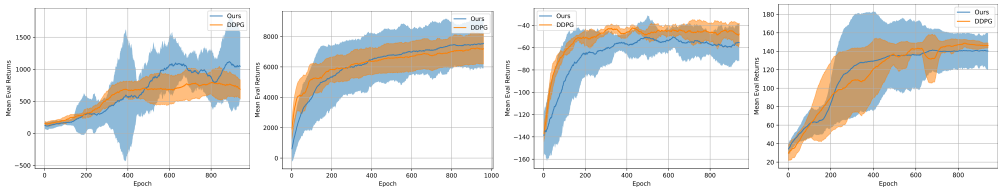


Figure 4: We introduce a bottleneck hidden layer of width $d_a + 1$ which is the output of the coordinate chart, ψ, i.e. the green colored base of the DNN. The output of this coordinate chart is fed into the manifold loss (Equation 3).

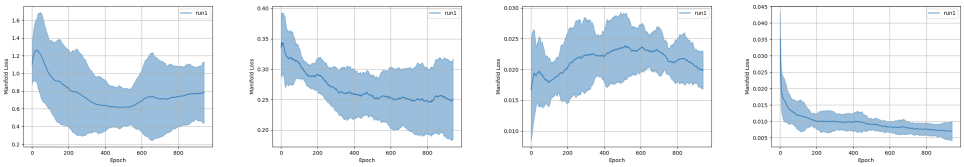


(a) Walker2D (b) Cheetah (c) Reacher (d) Swimmer

Figure 5: For all these environment we use $\alpha_\psi = 10^{-5}$, in comparison to $\alpha_\pi = 10^{-4}$, and the rest of the hyper-parameters are the same as reported by Lillicrap et al. (2016).

where α_π and α_ψ are the learning rates for the policy and the coordinate chart respectively. Note that update for parameters θ^ψ is then $\theta^\psi \leftarrow \theta^\psi - \alpha_\psi \nabla_{\theta^\psi} L_\psi \theta^\psi$, in addition to the update with respect to the objective for increasing the discounted return (See Appendix G and Algorithm 1 for further details). This is because for all $\theta_i \in \theta^\pi \setminus \theta^\psi$ we have $\nabla_{\theta_i} L(\theta^\psi) = 0$. We illustrate the architecture and how the representation feeds into the loss, for the policy network, in Figure 4. Note that the architecture and gradient updates for the DNN parameterising the Q function remains the same as used by Lillicrap et al. (2016), for control inputs, which is a two hidden layer DNN with 400 neurons in the first hidden layer, 300 in the second one and a one dimensional output.

We present results for 4 different MuJoCo environments: Cheetah, Walker2D, Swimmer and Reacher in Figure 5 and for three out of four of these environments the performance is either the same or better than the DDPG baseline. Our results strongly suggest that policy learning can be performed with a compressed isometric representation of dimesionality $d_a + 1$, learned using gradient updates parameterised by a deep neural network. This furthers our argument: there is a low dimensional structure to RL problems and it can be employed to learn more efficiently. Algorithmic details are given in Appendix G and ablation studies for the newly introduced hyper-parameter α_ψ in Appendix H, due to space limitations. In addition to this, we observe that the manifold loss (Equation 3) also drops steadily as training progresses, meaning that the representation being learnt, $\psi(s; \theta_\psi)$, is a low-dimensional isometric representation which retains the manifold geometry. The graphs for how the manifold loss, L_ψ, evolves in each case is given in Figure 6 along with the interpretation. We explain the reasons for Reachers' failure for our algorithm in Appendix I. In summary, to learn an isometric mapping to the Euclidean space the agent might require more than $\dim(\mathcal{S}_e)$ dimensions, for the case of Reacher. The additional constraint that we place, that the learnt coordinate chart has to be isometric, proves to be detrimental in this case. As has been done in manifold learning literature, we need methods for learning the low-dimensional mapping that do not rely on learning an isometry (Roweis & Saul, 2000; Zhang & Zha, 2004). We do not provide results for MuJoCo environments with images as inputs since building a K-nearest neighbors graph is computationally intensive for higher-dimensional data. We also need to apply better methods to approximate the geodesic distance between data points in the very high-dimensional setting which is beyond the scope of our current work.



(a) Walker2D (b) Cheetah (c) Reacher (d) Swimmer

Figure 6: We observe that the the loss L_ψ gradually decreases in all instances except Reacher where the performance is sub-par. For the Walker2D environment we see an increase in manifold error that matches the downward spike in performance in Figure 5 but the return for our method still surpasses the baseline in this case.

6 Related Work

There has been significant empirical work that assumes the state space to be a manifold in RL. The primary approach has been to study discrete state spaces as data lying on a graph which has an underlying manifold structure. Mahadevan & Maggioni (2007) provided the first such framework to utilise the manifold structure of the state space in order to learn value functions. Machado et al. (2017) and Jinnai et al. (2020) showed that PVFs can be used to implicitly define options and applied them to high dimensional discrete action MDPs (Atari games). Wu et al. (2019) provided an overview of varying geometric perspectives of the state space in RL and also show how the graph Laplacian is applied to learning in RL. Another line of work, that assumes the state space is a manifold, is focused on learning manifold embeddings or mappings. Several other methods apply manifold learning to learn a compressed representation in RL (Bush & Pineau, 2009; Antonova et al., 2020; Liu et al., 2021). Jenkins & Mataric (2004) extend the popular ISOMAP framework (Tenenbaum, 1997) to spatio-temporal data and they apply this extended framework to embed human motion data which has applications in robotic control. Bowling et al. (2005) demonstrate the efficacy of manifold learning for dimensionality reduction for a robot's position vectors given additional neighbourhood information between data points sampled from robot trajectories. At the same time, continuous RL has been applied to continuous robotic control (Doya, 2000; Deisenroth & Rasmussen, 2011; Duan et al., 2016). We apply continuous state, action and time RL as a theoretical mode to study the geometry of popular continuous RL environments for the first time, to the best of our knowledge.

7 Discussion and Conclusion

We have shown that that the dimensionality of the manifold is upper bounded by $d_a + 1$ and have empirically verified it (Figure 3). This proves that the popular manifold assumption (Mahadevan, 2005; Machado et al., 2017; 2018; Banijamali et al., 2018; Wu et al., 2019; Liu et al., 2021) holds under certain conditions in continuous-time reinforcement learning. It also shows that there is an underlying lower dimensional structure to the MDPs. Schmidt-Hieber (2019) show that, under assumptions over the function being approximated, the statistical risk deep ReLU networks approximating a function can be bounded by an exponential function of the manifold dimension. Similarly, Ji et al. (2022) show that the sample complexity of off-policy evaluation depends strongly on the intrinsic dimensionality of the manifold and weakly on the embedding dimension. Coupled with our result, these suggest that the complexity of RL problems and data efficiency would be influenced more by the dimensionality of the state manifold as opposed to the ambient dimension. Additionally, we demonstrate the applicability of this result in a practical setting by showing that a DDPG agent can learn efficiently in this highly compressed, low-dimensional space. Our newly introduced architecture and simultaneous low-dimensional representation learning along with policy learning performs on par or better than the baseline DDPG approach, for MuJoCo environments with sensor inputs. Overall, we show a theoretical bound on intrinsic dimensionality of continous RL problem and also show the efficacy of this low-dimensional representation in learning a policy. This open up room for new theoretical and empirical advances paving way for better DNN architecture design and representation learning algorithms.

8 REPRODUCIBILITY STATEMENT

We offer the following details for all the experiments we have performed, in the main body or appendix,: hyperparameters, sample sizes, GPU-hours, CPU-hours, code, neural network architectures, Python libraries used, input sizes, and external code bases. We also provide the code with instructions on running it in the supplementary material. All the details to run the code and its location are in Appendix K. All the hyperparameters, for our experiments in Section 5.2, can be found in appendices G, H and I.

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A ASSUMPTIONS

We list all the assumptions by section and consequently by theorems. We also provide some intuition on what these assumptions mean and how they limit our study.

Assumption made in Section 2.1 about continuous-time RL:

1. We assume that the transition function, f, is infinitely differentiable or smooth. This is done to ensure that the manifold it forms is also smooth. This might not always hold in practice but the transitions can be C^k smooth, meaning $k-$times differentiable. We use this assumption in the construction of a diffeomorphism in the definition of a manifold.
2. The set of actions, $\mathcal{A}$, is rectangular and open. This is pretty standard in practice for continuous environments. This much less an assumption but done so to simplify the analysis and avoid any confusion. The only reason we need the open part is to construct a diffeomorphism.

We do not state the entirety of the assumptions made in Section 3 but we provide further intuition for them:

1. We also use assumption that the Jacobian f is full rank. This assumption is needed for applying the implicit function theorem in the proof of Proposition B.2.
2. The no orbits assumption is a strong one but it is essential to proving Theorem 3.2. This might not hold strictly in practice but it can be argued that it holds almost always with probability 1, essentially the probability of an agent making an orbit is almost surely 0.
3. The action space restriction condition helps us construct a bijection for the proof of Theorem 3.2. Intuitively, the idea is that if two actions have the same local effect on how the agents state changes in some state then they can be collapsed into a single action for a fixed state s.

B PROOF OF THEOREM 3.2

We first state the implicit function theorem (for more details see theorem 3.3.1 in Chapter 3 by Krantz & Parks (2002)). In the statement of the implicit function theorem we use F to denote a general function, that satisfy the conditions stated in the theorem.

Theorem B.1. ***(Implicit Function Theorem)*** *Let $F : \mathbb{R}^{d_1+d_2} \to \mathbb{R}^{d_2}$ be a continuously differentiable function. Let $\mathbb{R}^{d_1+d_2}$ have coordinates $(\boldsymbol{x}, \boldsymbol{y})$ and fix a point $(\boldsymbol{x}_0, \boldsymbol{y}_0) = (x_{0,1}, ..., x_{0,d_1}, y_{0,1}, ..., y_{0,d_2})$ with $F(\boldsymbol{x}_0, \boldsymbol{y}_0) = \boldsymbol{0}$, where $\boldsymbol{0} \in \mathbb{R}^{d_2}$. The appropriate Jacobian is defined as:*

$$J_{F,\boldsymbol{y}}(\boldsymbol{x}, \boldsymbol{y}) = \begin{bmatrix} \frac{\partial F_1}{\partial y_1}(\boldsymbol{x}_0, \boldsymbol{y}_0) & \dots & \frac{\partial F_1}{\partial y_{d_2}}(\boldsymbol{x}_0, \boldsymbol{y}_0) \\ \vdots & \ddots & \vdots \\ \frac{\partial F_{d_2}}{\partial y_1}(\boldsymbol{x}_0, \boldsymbol{y}_0) & \dots & \frac{\partial F_{d_2}}{\partial y_{d_2}}(\boldsymbol{x}_0, \boldsymbol{y}_0) \end{bmatrix}.$$

If this Jacobian matrix is invertible then there exists an open set $V \subset \mathbb{R}^{d_1}$ containing $\boldsymbol{x}_0$ such that there exists a uniquely continuous differentiable function $h : V \to \mathbb{R}^{d_2}$ such that $h(\boldsymbol{x}_0) = \boldsymbol{y}_0$, and $F(\boldsymbol{x}, h(\boldsymbol{x})) = 0$ for all $\boldsymbol{x} \in V$.

Using the implicit function theorem we first prove our main result for the exact case where the dimensionality of the effective state space, $\mathcal{S}_e$, is $d_a + 1$. We do so under additional assumptions in the following proposition.

Proposition B.2. *Under the assumptions of Section 2.1 and 3 with the added assumption that the transition function, f, is injective in $\mathcal{A} \times (0, L)$, for some L, for fixed $s \in \mathcal{S}$ the effective state space, $\mathcal{S}_e \subset \mathbb{R}^{d_s}$, is a manifold of is $d_a + 1$.*

Proof. Given any state $s \in \mathcal{S}_e$ we can construct an open neighbourhood that maps to an open subset of $\mathbb{R}^{d_a+1}$. Since we know that $s \in \mathcal{S}_e$ there exists a state $s' \in \mathcal{S}_e$ such that $f(s', a, \epsilon) = s$ for some $a \in \mathcal{A}$ and $\epsilon \in (0, L)$. Now, for a fixed s' consider the map $\psi_{s'} : \mathcal{A} \times (\epsilon - \eta, \epsilon + \eta) \to \mathcal{S}_e$ such that $\psi_{s'}(a, t) = f(s', a, t)$ where $0 < \eta < \epsilon$, such that $\epsilon + \eta < L$, and $a \in \mathcal{A}$.

We need to show that this map, $\psi_{s'}$, is a diffeomorphism and maps to an open subset of S_e. Since the transition function, f, is smooth we have that $\psi_{s'}$ is also smooth in its range. Also note that f is injective $\mathcal{A} \times (0, L)$ for fixed s' and therefore it maps $\mathcal{A} \times (\epsilon - \eta, \epsilon + \eta)$ uniquely to a set U. This set U is a subset of $\mathcal{S}_e$ by definition. Note that U is open because $\mathcal{A} \times (\epsilon - \eta, \epsilon + \eta)$ is open because a bijection maps open sets to open sets. This leads to the conclusion that $\psi_{s'} : \mathcal{A} \times (\epsilon - \eta, \epsilon + \eta) \to U \subset \mathcal{S}_e$ is a smooth bijection. Thereby providing us a smooth parameterisation from $\mathbb{R}^{d_a+1}$ to U. This means that its inverse, $\psi_{s'}^{-1}$ exists. Now to show that this inverse is differentiable we apply the implicit function theorem.

Let $F(\mathbf{x}, \mathbf{y}, t) = f(s', \mathbf{y}, t) - \mathbf{x}$, note that s' is fixed as in above the variables are $\mathbf{x}, \mathbf{y}$ and t. The function F is restricted to the domain such that $x \in \mathcal{S}_e$, $y \in \mathcal{A}$ and $t \in (\epsilon - \eta, \epsilon + \eta)$. Since the Jacobian of f is full rank, by assumption, the appropriate Jacobian, $J_{F,[\mathbf{y},t]}$ as defined in Theorem B.1, is invertible and F is also continuously differentiable. Similarly, the condition $F(\mathbf{x}, \mathbf{y}, t) = \mathbf{0}$ holds for $\mathbf{x} = s$, $\mathbf{y} = a$ and $t = \epsilon$. Therefore, by the implicit function theorem there exists a unique function h and an open neighbourhood V containing $[a, \epsilon] \in \mathbb{R}^{d_a+1}$ such that $F(h(\mathbf{y}, t), \mathbf{y}, t) = 0$ and h is differentiable. Since h is unique we need to show that $h = \psi_{s'}^{-1}$ for the domain $V \cap (\mathcal{A} \times (\epsilon - \eta, \epsilon + \eta))$.

The proof follows from uniqueness of h. We have, for the domain $V \cap (\mathcal{A} \times (\epsilon - \eta, \epsilon + \eta))$, $F(\psi_{s'}^{-1}(\mathbf{y}, t), \mathbf{y}, t) = f(s', \mathbf{y}, t) - \psi_{s'}^{-1}(\mathbf{y}, t) = 0$. Therefore since h is unique and f is an injection for a fixed s' we have $h = \psi_{s'}^{-1}$.

We can similarly construct these diffeomorphisms from $\mathbb{R}^{d_a+1}$ to $U \subset \mathcal{S}_e$ for all $s \in \mathcal{S}_e$. Finally, by Definition 2.1 we have that $\mathcal{S}_e$ is a $d_a + 1$ dimensional manifold.

□

Now we prove the general case without the assumption of injectivity on f. To do so we construct an surjection $f' : \mathcal{S} \times \mathcal{A}' \times \mathbb{R}^+ \to \mathcal{S}$ where $\mathcal{A}' \subset \mathbb{R}^{d'}$ is an open set such that $d' \leq d_a$. We state the two additional assumptions made in Section 3. The first one being that for any policy $\pi \in \Pi$ we do not have any critical points or loops in the differential field defined by g_π. Formally, we have the following conditions $g_\pi(s) \neq \mathbf{0}$ for all $s \in \mathcal{S}$ and for a fixed policy π the solution for the equation $s_t^\pi = s$, if it exists, is unique in t. The second one is that if two actions have the same outcome at one state then they have the same outcome at all states. More formally, there exists an $r > 0$ such that for all $0 < \epsilon < r$, if we have $f(s, a_1, \epsilon) = f(s, a_2, \epsilon)$ for some fixed $a_1, a_2 \in \mathcal{A}$ and any one $s \in \mathcal{S}$ then it holds for all $\mathcal{S}$.

Under the assumptions of Section 2.1 and the ones stated above we restate the main theorem below before presenting the proof.

Theorem 3.2. *The set of effective states, $\mathcal{S}_e$, is a smooth manifold of dimensionality at most $d_a + 1$.*

Proof. With assumption 3 for every state we have a restriction $\mathcal{A}'_s$ that essentially turns $f(s, a, t)$ into a bijection for every $a \in \mathcal{A}'_s$. Now consider a function $f' : \mathcal{S}_e \times \mathcal{A}'_{s'} \times (\epsilon - \eta, \epsilon + \eta)$ which is a restriction of f's domain to $\mathcal{A}'_{s'} \times (0, T)$ for a fixed s'. Now for a fixed s, we can construct an open neighbourhood using $\psi_{s'} : \mathcal{A}'_{s'} \times (\epsilon - \eta, \epsilon + \eta)$ constructed as in Proposition B.2, $\psi_{s'}(a, t) = f'(s', a, t)$ such that $\psi_{s'}(a, \epsilon) = s$ for some $a \in \mathcal{A}'_{s'}$ and $\epsilon > \eta > 0$ and also $\epsilon + \eta < \tau$, where τ is as in assumption 2. Now we know that this is a bijection from assumptions 1, 2 and 3 in Section 3.1 as long as we choose ϵ and η small enough to satisfy the requirements for Proposition B.2. The restricted set $\mathcal{A}'_{s'}$ ensures that each action, for a fixed time t and s, maps to a unique state. Further, the assumption on no orbits ensures that for a fixed action $a \in \mathcal{A}'_{s'}$ there is a unique solution to $f(s', a, t) = s''$ for a fixed a, s' and s'' in t. Therefore, we constructed a full rank smooth bijection $\psi_{s'}$ which maps an open set $\mathcal{A}' \times (\epsilon - \eta, \epsilon + \eta)$ to an open subset of $\mathcal{S}_e$ for every $s \in \mathcal{S}_e$. We can now apply the same arguments of Proposition B.2 to argue that there exists a diffeomorphism $\psi_{s'}$ form an open set in $\mathcal{A}'_{s'} \times (\epsilon - \eta, \epsilon + \eta)$ to an open set in $\mathcal{S}_e$. This holds true for all s.

Finally, we conclude by stating that the dimensionality of the manifold is equal to the of $\dim(\mathcal{A}'_{s'} \times (\epsilon - \eta, \epsilon + \eta)) + 1$ which is less than or equal to $d_a + 1$. □

Finally, we prove Corollary 3.3. The proof is fairly straightforward following Definition 2.2 and Definition 3.1. Since the manifold $\mathcal{S}_e$ is defined as the union of all continuous curves from all possible smooth policies we can find a curve such that for any $s \in \mathcal{S}_e$ and $a \in \mathcal{A}$ for some policy $\pi(s) = a$ in

the neighborhood of s $\mathcal{S}_e \cap B(s, \epsilon)$ where $B(s, \epsilon)$ is a Euclidean ball of radius $\epsilon > 0$ centered at s. This would mean that for this policy, starting at s_0, there is a curve γ such that for some time t and some interval $\eta > 0$ we have $\gamma(t) = s$ and therefore $\dot{\gamma}(t) = v$ where $v \in T_s\mathcal{S}_e$. This vector v can now be uniquely mapped to the action and therefore can be labeled v_a as in Corollary 3.3. We also note that this vector is unique independent of the choice of ϵ or η.

C Dimensionality Estimation as in Facco et al. (2017)

We describe the algorithm for dimensionality estimation in context of sampled data from the state manifold $\mathcal{S}_e$. Let the dataset be randomly sampled points from a manifold $\mathcal{S}_e$ embedded in $\mathbb{R}^{d_s}$ denoted by $\mathcal{D} = \{s_i\}_{i=1}^N$. For a point s_i from the dataset $\mathcal{D}$ let $\{r_{i,1}, r_{i,2}, r_{i,3}, ...\}$ be a sorted list of distances of other points in the dataset from s_i and they set $r_0 = 0$. Then the ratio of the two nearest neighbors is $\mu_i = r_{i,2}/r_{i,1}$ where $r_{i,1}$ is the distance to the nearest neighbor in $\mathcal{D}$ of s_i and $r_{i,2}$ is the distance to the second nearest neighbor. Facco et al. (2017) show that the logarithm of the probability distribution function of the ratio of the distances to two nearest neighbors is distributed inversely proportional to the degree of the intrinsic dimension of the data and we follow their algorithm for estimating the intrinsic dimensionality. We describe the methodology provided by Facco et al. (2017) in context of data sampled by an RL agent from a manifold. Without loss of generality, we assume that $\{s_i\}_{i=1}^N$ are in the ascending order of r_i. We then fit a line going through the origin for $\{(\log(\mu_i), -\log(1 - i/N)\}_{i=1}^N$. The slope of this line is then the empirical estimate of $\dim(\mathcal{S}_e)$. We refer the reader to the supplementary material provided by Facco et al. (2017) for the theoretical justification of this estimation technique. The step by step algorithm is restated below.

1. Compute $r_{i,1}$ and $r_{i,2}$ for all data points i.
2. Compute the ratio of the two nearest neighbors $\mu_i = r_{i,2}/r_{i,1}$.
3. Without loss of generality, given that all the points in the dataset are sorted in ascending order of μ_i the empirical measure of cdf is i/N.
4. We then get the dataset $\mathcal{D}_{\text{density}} = \{(\log(\mu_i), -\log(1 - i/N)\}$ through which a straight line passing through the origin is fit.

The slope of the line fitted as above is then the estimate of the dimensionality of the manifold.

D DDPG Background

An agent trained with the DDPG algorithm learns in the discrete time but with continuous states and actions. With abuse of notation, a discrete time and continuous state and action MDP is defined by the tuple $\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, f_r, s_0, \lambda)$, where $\mathcal{S}, \mathcal{A}$, s_0 and f_r are the state space, action space, start state and reward function as above. The transition function $P : \mathcal{S} \times \mathcal{A} \times \mathcal{S}$ is the transition probability function, such that $P(s, a, s') = \Pr(S_{t+1} = s'|S_t = s, A_t = a)$, is the probability of the agent transitioning from s to s' upon the application of action a for unit time. The policy, in this setting, is stochastic, meaning it defines a probility distribution over the set of actions such that $\pi(s, a) = \Pr(A_t = a|S_t = s)$. The discount factor is also discrete in this setting such that an analogous state value function is defined as

$$v^\pi(s_t) = \mathbb{E}_{s_l, a_l \sim \pi, P}\left[\sum_{l=t}^{T} \lambda^{l-t} f_r(s_l, a_l)|s_t\right],$$

which is the expected discounted return given that the agent takes action according to the policy π, transitions according to the discrete dynamics P and s_t is the state the agent is at time t. Note that this is a discrete version of the value function defined in Equation 2. The objective then is to maximise $J(\pi) = v^\pi(s_0)$. One abstraction central to learning in this setting is that of the *state-action value function* $Q^\pi : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$, for a policy π, is defined by:

$$Q^\pi = \mathbb{E}_{s_l, a_l \sim \pi, P}\left[\sum_{l=t}^{T} \lambda^{l-t} f_r(s_l, a_l)|s_t, a_t\right],$$

which is the expected discounted return given that the agent takes action a_t at state s_t and then follows policy π for its decision making. An agent, trained using the DDPG algorithm, parametrises the policy and value functions with two deep neural networks. The policy, $\pi : \mathcal{S} \to \mathcal{A}$, is parameterised by a DNN with parameters θ^π and the action value function, $q : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$,is also parameterised by a DNN with ReLU activation with parameters θ^Q. Although, the policy has an additive noise, modeled by an Ornstein-Uhlenbeck process (Uhlenbeck & Ornstein, 1930), for exploration thereby making it stochastic. Lillicrap et al. (2016) optimise the parameters of the Q function, θ^Q, by optimizing for the loss

$$L_Q = \frac{1}{N}\sum_{i=1}^{N}(y_i - Q(s_i, a_i; \theta^Q))^2, \tag{5}$$

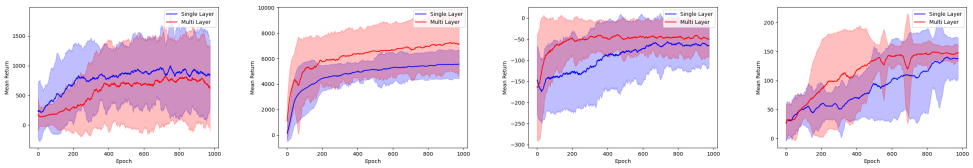
where y_i is the target value set as $y_i = r_i + \lambda Q(s'_{i+1}, \pi(s_{i+1}; \theta^\pi); \theta^Q)$. The algorithm updates the parameters θ^Q by $\theta^Q \leftarrow \theta^Q + \alpha_Q \nabla_{\theta^Q} L_Q$, where L_Q is defined as in Equation 5. The gradient of the policy parameters is defined as

$$\nabla_{\theta^\pi} J(\theta^\pi) = \frac{1}{N}\sum_i \nabla_a Q(s, a; \theta^Q)|_{s=s_i, a=\pi(s_i)} \nabla_{\theta^Q} \pi(s; \theta^\pi)|_{s=s_i}, \tag{6}$$

and the parameters θ^π are updated in the direction of increasing this objective.

E DDPG MODIFIED ARCHITECTURE COMPARISON

We provide the comparison between single hidden layer network and multiple hidden layer network because our results in section 4 are for single hidden layer. The same architecture is used by Lillicrap et al. (2016) for the policy and value function DNNs which is two hidden layers of width 300 and 400 with ReLU activation. Here we provide the comparison to single hidden layer width 400 and MUP (Yang & Hu, 2020) with GELU activation for the architecture used by Lillicrap et al. (2016). We provide this comparison in Figure 7 and note that the performance remains comparable for both the architectures. All results are averaged over 6 different seeds. We use a PyTorch based implementation for DDPG with modifications for MUP parametrisation and the use of GELU units. The base implementation of the DDPG algorithm can be found here: https://github.com/rail-berkeley/rlkit/blob/master/examples/ddpg.py. The hyperparameters are as in the base implementation.



(a) Walker2D (b) Cheetah (c) Reacher (d) Swimmer

Figure 7: Comparison of single hidden layer (blue) and multiple hidden layer (red) architectures for DNNs.

F SAMPLING STRATEGY AND GEODESIC DISTANCE ESTIMATION

We use graphs as a discrete abstraction of manifolds to sample efficiently whilst preserving *local properties* of the sampled nodes. In many representation learning aprroaches the main objective is to learn to map individual data points to dense vectors in a low dimensional space via stochastic gradient descent (Mikolov et al., 2013; Perozzi et al., 2014; Grover & Leskovec, 2016). One of the primary objectives is to preserve relationships between data points. Graphs, with individual data points mapping to nodes and the relationships between them ecnoded as the edges, are used as an abstraction to represent the whole dataset with all the charecteristic relationships. In our case we seek to preserve *local isometry* in the learnt mapping, ψ. Meaning, given a point $s \in \mathcal{D} \subset \mathcal{S}_e$ we would like to preserve the geodesic distance between s and the points in its "neighbourhood" upon being mapped to a lower dimensional representation.

We first define the graph that is a discrete representation the state manifold, $\mathcal{S}_e$, and state the above objective more formally. An undirected graph $\mathcal{G} = (V, E)$ consists of nodes and edges, where $V = \{v_i\}_{i=1}^{N_V}$ are the individual nodes and an edge $e = (v_i, v_j) \in E$ implies that there is a an edge between the nodes v_i and v_j for some i, j. Since the graph, $\mathcal{G}$, is undirected $(v_i, v_j) \in E \implies (v_j, v_i) \in E$. Given a node, v_i, the one-hop neighborhood of this node is defined as all the nodes $v_j \in V$ such that $(v_i, v_j) \in E$. Now we define a graph, deonted by $\mathcal{G}_\mathcal{D} = (\mathcal{D}, E_\mathcal{D})$ that forms a discrete abstraction over the manifold $\mathcal{S}_e$ using the dataset $\mathcal{D}$. We first set all the ndoes to be the states in our dataset, $\mathcal{D}$. A datapoint's one hop neighbourhood as the k_{nn} points nearest by the Euclidean distance in the dataset $\mathcal{D}$. This means that for every state $s_i \in \mathcal{D}$ we have k_{nn} edges to k_{nn} distinct nearest points in $\mathcal{D}$. This is a k_{nn}-nearest neighbors construction of the graph from a dataset $\mathcal{D}$, sampled from a manifold (Yan et al., 2007; Dong et al., 2011). We augment the edges of this graph $\mathcal{G}_\mathcal{D}$ with an additional set of edge attributes, the Euclidean distance between two points $(s_i, s_j) \in E_\mathcal{D}$ i.e. $||s_i - s_j||_2$. Therefore, the augmented graph now becomes $\mathcal{G}_\mathcal{D} = (\mathcal{D}, E_\mathcal{D}, A_\mathcal{D})$ where $A_\mathcal{D}$ is an ordered set with the Euclidean distances between the two nodes in $E_\mathcal{D}$.

For most practical applications, the number nodes of this graph $\mathcal{G}_\mathcal{D}$ is in thousands and consequently the number of edges are k_{nn} times the number of nodes. Since we learn the mapping ψ using SGD we can sample batches of state pairs and the distances between them. To do so we randomly sample a subset of states from $\mathcal{D}$. We then construct a subgraph which consists of nodes k_h hops away from these randomly subsampled points. We then use this randomly sampled subgraph to compute the pairwise distance between them using breadth first search. We denote this procedure by the function Random-K-Hop-Subgraph($\mathcal{G}_D, k_h$). Since this randomly sub-sampled graph is much smaller in size whilst preserving the distances we postulate that the distance thus obtained between pairs of states, as the sum of the distance attributes of the shortest paths, is a good approximation of the geodesic distance $d_{\mathcal{S}_e}$. We remind the reader that this geodesic distance is needed for the manifold loss introduced in Equation 3. This three step procedure: **1)** sampling data on the manifold, **2)** constructing a k_{nn}-nearest neighbors graph from this data, and **3)** randomly sampling k_h-hop subgraphs, is illustrated with an example of the Swiss roll manifold in Figure 8.

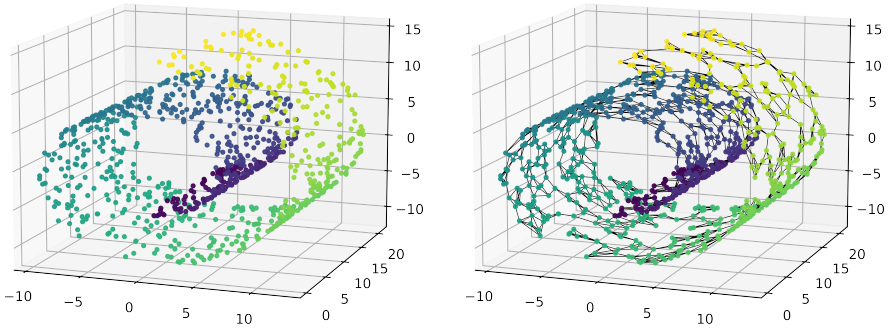
G Algorithmic Details

An RL agent, trained using the DDPG algorihm, collects data from trajectories as tuples: (s, a, s', r) where s is the state at which the agent takes an action a and transitions to state s' and obtains the reward r. The algorithm stores a buffer of these tuples and therefore we have access to the set of available states s, sampled from the state manifold $\mathcal{S}_e$. As described in the previous section, our algorithms requires a dataset sampled from the manifold to estimate the manifold loss in Equation 3. Therefore our algorithm subsamples the states from this buffer to obtain the aforementioned dataset, $\mathcal{D}$, at every episode. Then our algorithm (Algorithm 1) uses this dataset to obtain a sample of pairs of states and geodesic distances between these states, as described in the previous section, to perform SGD on the parameters of the mapping to the low-dimensional space, θ_ψ, on the loss L_ψ. All the results have the same values for $k_{\text{nn}} = 6, k_h = 4$ and we use a batch size of 128 for the subsampling the graphs as described in Appendix F for the function Random-K-Hop-Subgraph. These were obtained after manual tuning. The other parameters, are set to the defualt ones for DDPG $\tau = 0.01$, $\lambda = 0.99$, $\alpha_Q = 0.001$ and the replay buffer size is 10^6. We provide details for running the code in Appendix K.

H Additional Experiments and Ablation Studies

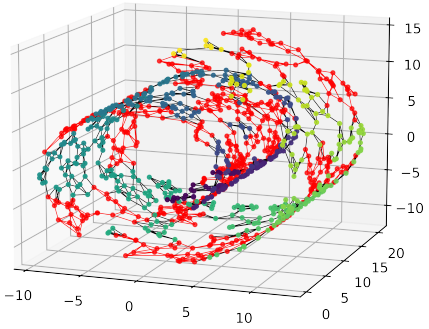
All results reported here that are reported are an average over 6 different seeds. For all but the Reacher environment we see the manifold loss decrease as training progresses, as expected. Meaning the agent is able to learn a low-dimensional isometric representation, ψ, as well as a policy that operates on this low-dimensional input. We observe that for the Reacher environment our Algorithm is unable to simulataneously learn a low dimensional mapping and a policy. This is a true despite searching across all the hyperparameters.

We present the ablation study over the hyperparameter α_ψ in Figure 9. This suggests that further increasing the learning rate, α_ψ, improves performance of the agent, in case of walker but it begins to detireorate after a certain point, $\alpha_\psi = 1.5$.



(a) First we obtain a set of points sampled from a manifold.

(b) In the second step, edges are drawn between the $k_{\text{nn}} = 4$ nearest points.



(c) Finally, nodes and edges (in red) are subsampled based on the $k_h = 2$ hop neighbourhood of randomly sampled nodes.

Figure 8: The three step sub-sampling for estimating geodesic distances and batched learning in SGD is illustrated with the example of the Swiss-roll manifold. We use the `scikit-learn` package (Pedregosa et al., 2011) for sampling the data, `torch-geometric` package for generating k_{nn}-nearest neighbors graph and also for obtaining the k_h-hop subgraphs (Fey & Lenssen, 2019).

Algorithm 1 DDPG with Manifold Representaion Learning

π, Q parameterised by θ^{π}, θ^{Q} respectively.
$\theta^{\pi}, \theta^{Q} \sim \Pr(\theta)$
Initialize the parameters of the target $\theta^{\pi'}, \theta^{Q'} \leftarrow \theta^{\pi}, \theta^{Q}$.
Initialise replay buffer B
for Episode 1 to Max Episodes **do**
  Initialise the Ornstein-Uhlenbeck process for exploration noise: X
  for Time step t, 0 to T **do**
    Set action $a_t = \pi(s_t; \theta^{\pi}) + X_t$.
    Execute action a_t and observe r_t, s_{t+1} storing it in B
    Sample a minibatch of N transitions (s_i, a_i, r_i, s_{i+1}) from B
    Compute the loss L_Q and update the parameters θ^{Q}
    Construct the dataset $\mathcal{D}$ from all the states s_i from the sampled N tuples
    Construct the graph $\mathcal{G}_{\mathcal{D}}$ using k_{nn}-nearest neighbors
    Subsample graph $\mathcal{G}'_{\mathcal{D}'}(\mathcal{D}', E_{\mathcal{D}'}, \mathcal{A}'_{\mathcal{D}'}) =$ Random-K-Hop-Subgraph$(\mathcal{G}_{\mathcal{D}}, k_h)$
    Obtain the set of state pairs and geodesic distances, from $\mathcal{G}'_{\mathcal{D}'}$, to calculate L_{ψ}
    Update the policy as in Equation 3:

$$\theta^{\pi} \leftarrow \theta^{\pi} + \alpha_{\pi} \nabla_{\theta} J(\pi) - \alpha_{\psi} \nabla_{\theta} L_{\psi}$$

    Update the target networks:

$$\theta^{Q'} \leftarrow \tau \theta^{Q} + (1-\tau)\theta^{Q'}$$
$$\theta^{\pi'} \leftarrow \tau \theta^{\pi} + (1-\tau)\theta^{\pi'}$$

  end for
end for

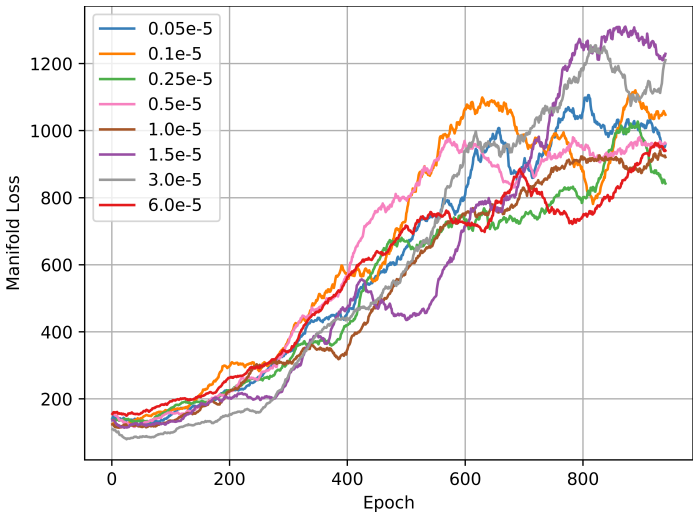


Figure 9: We observe the effect of increasing the hyperparameter α_{ψ} on the discounted return in the Walker2D environment.

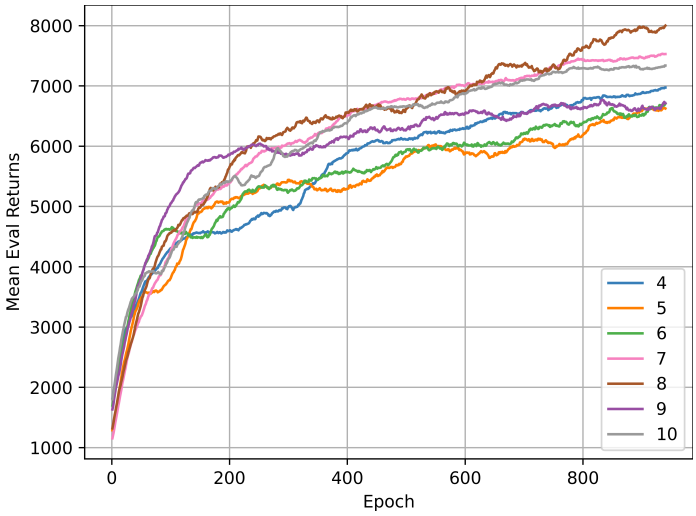
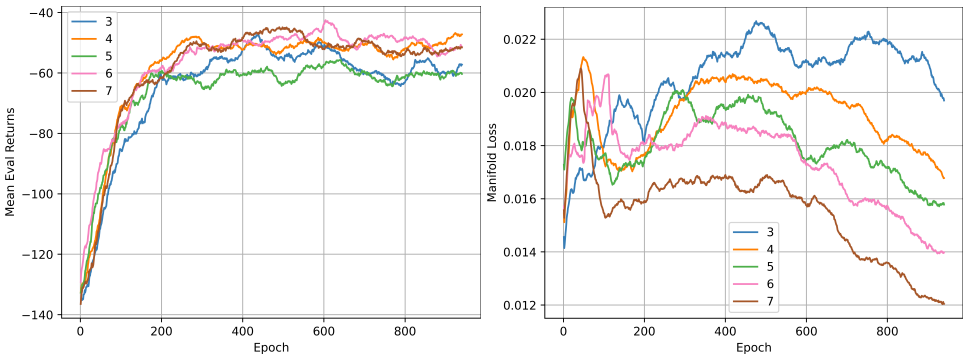


Figure 10: The discounted return for varying the width of the bottleneck layer for the Cheetah domain with $d_a + 1 = 7$. We see the performance peaks at width 8.



(a) Mean Evaluation Returns (b) Manifold Loss

Figure 11: We observe that the manifold loss decreases as we increase the width of the bottleneck layer and the performance improves. All the hyper-parmaeters are the same as in Appendix G.

Finally, we demonstrate the effects of changing the width of the bottleneck layer on the Cheetah domain in Figure 10. Most importantly, we observe that the performance peaks at width equal to 8, with both 7 and 8 have similar returns. From the results for dimensionality estimation, in Figure 3, we know that the estimate lies between 7 and 8. This suggests that in case of Cheetah there is an optimal isometric "compression" that allows the agent to perform optimally and better than the baseline. This furthers our argument that an RL agent can learn efficiently on this low dimensional manifold by utilising the underlying structure. The error margins are omitted for the clarity of exposition since there are multiple curves on the same graph.

I Explaining Failure in Reacher Environment

Here we explain the failure case of the Reacher environment. As noted in Section 5.2 isometry is a stronger condition that mere diffeomorphism. The Nash embedding theorem states that the an m-dimensional C^1 manifold can be embedded isometrically into a Euclidean space of dimensionality at most $m(m+1)$ or $(3m+11)/2$ (Nash, 1954), therefore the embedding dimension required for learning an isometric embedding for $\mathcal{S}_e$ might be greater than $d_a + 1$. For example, a circle which is a 1D manifold in 2D Euclidean space cannot be isometrically embedded into 1D. Therefore, the objective we train on is stronger than learning a coordinate chart. We hypothesize that for the

reacher environment the agent is unable to learn this isometry. As reported in Figure 11, as we increase the width, and therefore the embedding dimension, the manifold loss decreases and the agents performance as measured by mean discounted return improves. As we increase the width to 7 the performance is on par with the baseline approach. The error margins are omitted for the clarity of exposition since there are multiple curves on the same graph.

J COMPUTE REQUIREMENTS

For each one of our experiments we perform 6 different runs with varying seeds to obtain the results. Since experiments in Section 5.1 only require trajectories we reuse the trajectories sampled form the ReLU and GELU comparison experiments in Appendix E. For all the experiments in Appendix E we required approximately 180 hours of processing time on NVIDIA GeForce RTX 3090 GPUs which have 24 GB of RAM. We also run two runs of the DDPG algorithm simultaneously on each GPU, owing to the 24 GB RAM availability per GPU, which cuts our run time into half.

K STEPS FOR RUNNING THE CODE AND GPU HOURS

All code is in python and was tested for python 3.6. We use the pytorch library for the ease of defining and training DNNs (Paszke et al., 2019) and pytorch_geometric (Fey & Lenssen, 2019) for all graph operations.

We provide the implementation of DDPG using GELU units in the `code/rlkit/` folder of our supplementary material To install the environment we recommend installation using the `setupy.py` file present in the folder. For running the experiment, there are multiple files in the `code/rlkit/examples/smooth_ddpg/ddpg*.py`, each one uses a different architecture and environment details of which can be found within the file. To execute the code, e.g. for `ddpg_arch_2.py`, run the following command from the rlkit folder:

```
python examples/smooth_ddpg/ddpg_arch_2.py 115 gelu
```

where "115" is the seed and "gelu" argument means the DNN thus instantiated uses gelu activations. Our code samples trajectories and the location of the folder can be specified in the file `path_collector.py`

The code for dimensionality estimation using neighborhood data is fairly simple and only requires version 1.1.1 of the python package `scikit-learn` (Pedregosa et al., 2011). It is provided in `code/data-processing/dim-estimate`. The main file is `dim-estimate.py`. It expects a pickle file which is an array of all states sampled for an agent. The code for cleaning the samples, from runs of the DDPG code as described above, and acquiring them in the required format can be found in the file `run_data_processing.py`.

The code for the simultaneous dimensionality reduction and policy learning can be found in the folder `code/rlkit/examples/manifold_learning/ddpg*.py`. The implementation for graph creation and sampling procedure using pytorch_geometric is in the file `code/rlkit/rlkit/torch/manifold/mrl_ddpg.py`. The various architectures used for the policy network can be found in the folder `code/rlkit/rlkit/archs_dir/manfiold_arch`.

Finally, the code for obtaining the illustrations in Figure 8 are in the folder `code/rlkit/illustration_scripts`.

For the results and all its ablations in Section 5.2, we ran multiple instances of the modified DDPG algorithm and the baseline DDPG algorithms for 6 seeds each for 1000 epochs on cloud instances with Nvidia 3090 Ti GPUs with 24 GB memory, and CPUs with 8 cores and 16 GB RAM. Each run takes about 3 hours each. This means we utilised about 600 GPU hours, including hyperparameter tuning. The results in Section 5.1 were obtained from the trajectories sampled from various DDPG runs and took about 20 CPU hours on an 8 core machine.