Synthesizing Neural Network Controllers with Probabilistic Model-Based Reinforcement Learning

Juan Camilo Gamboa Higuera, David Meger and Gregory Dudek
School of Computer Science
Centre for Intelligent Machines
McGill University
{gamboa,dmeger,dudek}@cim.mcgill.ca

1 Introduction

Model-based reinforcement learning (RL) is an attractive framework for addressing the synthesis of controllers for mobile robots; due to its promise of data-efficiency. By using experience data to fit state-transition dynamics models, an RL agent can search for good controllers using these models to evaluate policies in simulation. This allows for minimizing costly trials on the target robot platform. Minimizing interactions, however, means that experience datasets won't be large enough to obtain accurate dynamics models. Bayesian models are very helpful in this situation. Instead of requiring an accurate model, the RL agent may keep track of a distribution of dynamics models that are compatible with its experience. Evaluating a controller now involves quantifying its performance over the dynamics model distribution: a good controller should perform well on average when drawing a model from this distribution, to improve its chances of working in the real world. Two successful applications of this idea are the PILCO [1] and Deep-PILCO algorithms.

PILCO [1] uses Gaussian Process (GP) models to fit one-step dynamics and networks of radial basis functions (RBFs) for feedback policies. PILCO has been shown to perform very well with little data in benchmark simulated tasks and on real robots [1]. We have used PILCO successfully for synthesizing swimming controllers for an underwater swimming robot [2]. However, PILCO is computationally expensive. Model fitting scales $O(Dn^3)$ and simulated rollouts scale $O(D^3n^2)$, where n is the dataset size and D is the number of state dimensions, limiting its applicability to scenarios with small datasets and a low number of dimensions.

Deep-PILCO [3] aims to address these shortcomings by employing Bayesian Neural Networks (BNN), implemented using binary dropout [4, 5]. Deep-PILCO uses BNNs to fit a dynamics model, and performs a sampling-based procedure for simulation. This Policy Search and model learning are done via stochastic gradient optimization: computations with linear scaling in the dataset size and state dimensionality. Deep-PILCO has been shown to result in better performing policies for the cart-pole swing-up benchmark task, but reduced data efficiency when compared with PILCO on the same task.

In this work, we extend on the results of [3]. We demonstrate that Deep-PILCO can match the data efficiency of PILCO on the cart-pole swing-up task with a small number of heuristics to stabilize optimization. We demonstrate that using neural network controllers improves the data efficiency of Deep-PILCO. We also show that using Log-Normal multiplicative noise [6] removes the need for searching for the appropriate dropout rate, and outperforms the original version of Deep-PILCO with binary dropout on the cart-double pendulum swing-up task.

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[1] Probabilistic Inference and Learning for COntrol

2 Methods

We follow the problem definition in [1, 3]. We assume target systems that can be modeled with an unknown discrete-time first-order dynamics equation $\mathbf{x}_{t+1} = f(\mathbf{x}_t, \mathbf{u}_t)$, where f is unknown, $\mathbf{x}_t \in \mathbb{R}^D$ is the state of the system and $\mathbf{u}_t \in \mathbb{R}^U$ is the applied control, at time step t. The goal is to find the parameters θ of a control policy π_θ that minimize a state-dependent cost function c accumulated over a given time horizon H,

$$\arg\min_\theta \quad J(\theta) = \mathbb{E}_\tau \left\{ \sum_{i=1}^H c(\mathbf{x}_t) \right\}. \tag{1}$$

The expectation is taken over the trajectory distribution $p(\tau) = p(\mathbf{x}_1, \mathbf{u}_1, ..., \mathbf{x}_H, \mathbf{u}_H)$. In PILCO, the expectation over trajectories is replaced by an expectation over individual state distributions $p(\mathbf{x}_1), ..., p(\mathbf{x}_H)$ which are modelled as Gaussian. Simulation consists of finding the parameters of each $p(\mathbf{x}_t)$, its mean and covariance, by analytical integration. The cost function is approximated as $J(\theta) \approx \sum_{i=1}^H \mathbb{E}_{\mathbf{x}_t} \{c(\mathbf{x}_t)\}$. This is an approximation to $p(\tau)$ as a multivariate Gaussian with block-diagonal covariance, assuming deterministic controllers.

Deep-PILCO uses the same approximation for the cost, but the state distributions $p(\mathbf{x}_t)$ are obtained empirically from simulated trajectories. We obtain K simulated trajectories from the following model:

$$\begin{aligned}
\mathbf{x}_1^{(k)} &\sim p(\mathbf{x}_1), & f^{(k)} &\sim p(f), \\
\mathbf{u}_t^{(k)} &\sim \pi_\theta\left(\mathbf{u}_t^{(k)} | \mathbf{x}_t^{(k)}\right), & \mathbf{y}_{t+1}^{(k)} &\sim p(\mathbf{x}_{t+1}^{(k)} | \mathbf{x}_t^{(k)}, \mathbf{u}_t^{(k)}, f^{(k)}), \\
& & \mathbf{x}_{t+1}^{(k)} &\sim N(\mathbf{x}_{t+1}^{(k)} | \mu_{\mathbf{y}_t}, \Sigma_{\mathbf{y}_t}).
\end{aligned} \tag{2}$$

The sampling from the dynamics model distribution $p(f)$ is approximated by sampling the weights of a BNN fit to the experience data. The last step in Eq. 2 corresponds to sampling from the moment-matched Gaussian distribution of the output of the dynamics.

2.1 Stabilizing the optimization procedure

2.1.1 Common random numbers (CRN) and PEGASUS policy evaluation

The convergence of Deep-PILCO is highly dependent on the variance of the estimated gradient $\nabla_\theta \hat{J}(\theta) = \frac{1}{K} \sum_k^K \nabla_\theta J(\theta | \hat{f}^{(k)}, \mathbf{x}_1^{(k)})$. The variance of this gradient is, among other things, dependent on $p(\mathbf{x}_1)$, the random numbers used for Monte Carlo integration, and the number of particles K. In our initial experiments we increased K from 10 to 100, and found it to improve convergence with small penalty on running time.

Increasing the number of particles also enables us to further reduce variance by using *common random numbers* (CRN). The generative model in Eq. 2, implemented with BNNs in Deep-PILCO, relies on the re-parametrization trick [7] to propagate policy gradients over the simulation horizon. If we provide the random numbers for the policy evaluation step of Deep-PILCO, we obtain a variant of the PEGASUS[2] algorithm [8]. This approach requires intermediate moment-matching and re-sampling steps. To reduce the impact of biases from deterministic policy evaluations, we re-sample the random numbers after each trial, but they remain fixed during the policy optimization phase.

2.1.2 Gradient Clipping

As noted in [3], the recurrent application of BNNs to implement the generative model in Eq. 2 can be interpreted as a Recurrent Neural Network (RNN) model. As such, Deep-PILCO is prone to suffer from vanishing and exploding gradients [9], especially when dealing with tasks that require long time horizon or very deep models for the dynamics and policy. Although numerous techniques have been proposed in the RNN literature, we found the gradient clipping strategy to be effective in our experiments; as shown in Figure 3b.

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[2]Policy Evaluation-of-Goodness And Search Using Scenarios

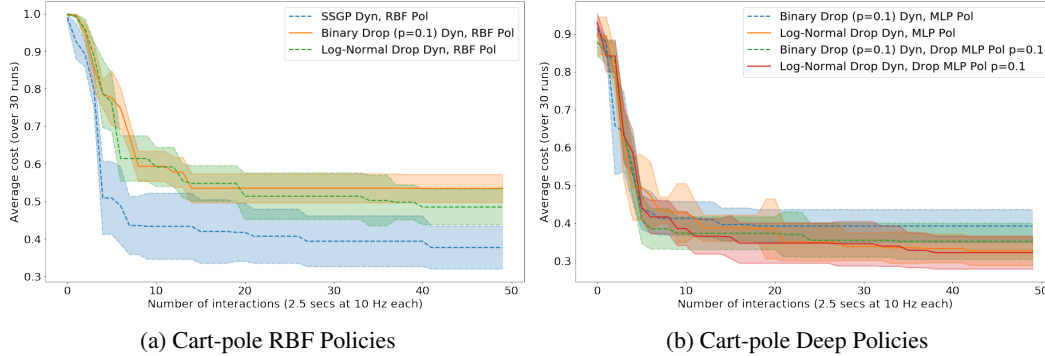(a) Cart-pole RBF Policies   (b) Cart-pole Deep Policies

Figure 1: Cost per trial on the cart-pole swing-up task. The shaded regions correspond to half a standard deviation (for clarity). In (a), RBF policies are learned with various methods, as has been examined by prior work. NN policies are learned in (b), which demonstrate that Deep-PILCO, with deterministic policy evaluations, can match the data efficiency of PILCO in the cart-pole task.

2.2 Training neural network controllers

While Deep-PILCO had been limited to training single-layer Radial Basis Function policies, the application of gradient clipping and CRNs allows stable training of deep neural network policies, opening the door for richer behaviors. We found that adding dropout regularization to the policy networks improves performance. During policy evaluation, we sample from policies with a similar scheme to that used for dynamics models. For each particle, we sample one dynamics model and one policy, and keep them fixed during policy evaluation. This can be viewed as attempting to learn a distribution of controllers that are likely to perform well over plausible dynamic models. We decided to make the policy stochastic during execution, by using a single dropout sample of the policy at every time step. This provides a limited amount of exploration, which we found beneficial, in particular, for the double cart-pole swing-up task.

2.3 BNNs with Log-Normal multiplicative noise

Deep-PILCO with binary dropout requires tuning the dropout probability to a value appropriate for the model size. We experimented with other BNN models [10, 11, 6] to enable learning the dropout probabilities from data. The best performing method in our experiments was using Log-Normal dropout with a truncated log-uniform prior $\text{LogU}_{[-10,0]}$. The multiplicative noise is constrained to values between 0 and 1 [6]. Other methods we may explore in the future include Concrete Dropout [12] and Beta distributed multiplicative noise.

3 Results

We tested the improvements, described in Section 2, on two benchmark scenarios: swinging up and stabilizing an inverted pendulum on a cart, and swinging up and stabilizing a double pendulum on a cart. The first task was meant to compare performance on the same experimental setup as [3]. We chose the second scenario to compare the methods with a harder long-term prediction task; due to the chaotic dynamics of the double-pendulum.

Figure 1 summarizes our results for the cart-pole domain. On the left hand side we compare PILCO with sparse spectrum GP regression [13] for the dynamics, with Deep-PILCO using BNN dynamics; one using binary dropout with dropout probability $p = 0.1$, and the other using Log-Normal dropout with a truncated log-uniform $\text{LogU}_{[-10,0]}$. The BNN models are ReLU networks with two hidden layers of 200 units and a linear output layer. We do not discard older data during training. The learning rate was set to 10^{-4} for model fitting and 10^{-3} for policy learning. While fitting the models to experience data, we learn a homoscedastic measurement noise parameter for each output dimension. This noise is used to corrupt the input to the policy. The policies are RBF networks with 30 units. The first interaction with the system corresponds to applying uniformly-at-random controls. On the right we see a comparison of various neural network policies in the same task, using the same BNN dynamics as on the left . The policy networks are ReLU networks with two hidden
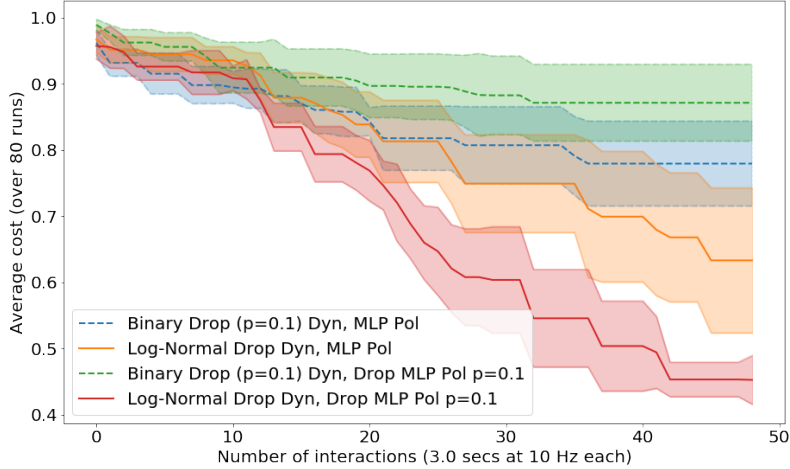
Figure 2: Cost per trial on the double cart-pole swing-up task. The shaded regions correspond to half a standard deviation (for clarity). This demonstrates the benefit of using Log-Normal multiplicative noise for the dynamics with dropout regularization for the policies

layers of 200 units. The initial experience consists of a single trial with uniformly random controls. The results show that training complex neural network controllers provide better performance than PILCO or Deep-PILCO with RBF controllers, without reducing data efficiency. The code used in these experiments is avalable at `https://github.com/juancamilog/kusanagi`.

Figure 2 illustrates the effect of the techniques on the more complicated double cart-pole swing-up task. The setup is similar to the cart-pole task, but we change the networks architecture slightly as the dynamics are more complex. The dynamics models are ReLU networks with 4 hidden layers of 200 units and a linear output layer. The policies are ReLU networks with four hidden layers of 50 units. The learning rate for policy learning was set to 10^{-4} for this experiment. In this case, the differences in performance are even more pronounced. Our proposed method converged after 42 trials, corresponding to 126 s of experience at 10 Hz. This is close to the 84 s at 13.3 Hz reported in [14]. We are currently preparing experiments with these methods on more complex environments, including the AQUA robot [2]. Notably, making the policies stochastic via dropout appears to improve their performance when using log-normal multiplicative noise.

(a) CRN comparison
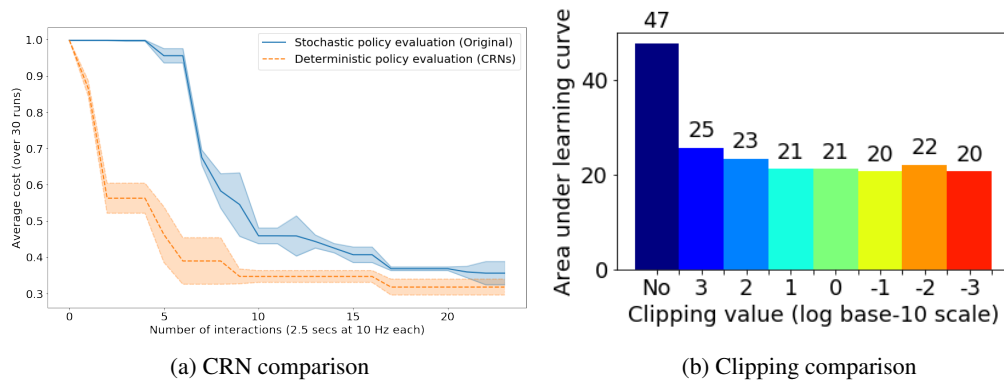
(b) Clipping comparison

Figure 3: (a) Illustrates the benefit of fixing random numbers for policy evaluation (as in [8]) versus using stochastic policy evaluations (as in the approach of [3]), and (b) Shows the area under the learning curve for the cart-pole (sum of average cost across all trials – lower is better) for various gradient clipping strategies.

Figure 3a shows a comparison between using fixed random numbers and re-sampling a new set of particles at each optimization step, for the cart-pole balancing task. In this experiment, we use a similar setup to the one for the results in Figure 1. The initial experience consists of one trial with randomized controls and one trial applying the initial policy. The learning rate was set to 10^{-4}.

4

While previous experiments combining PILCO with PEGASUS were unsuccessful [14], we found the combination of Deep-PILCO with this type of deterministic policy evaluation to be necessary for convergence when training neural network policies. We did not find parameters for Deep-PILCO, with stochastic policy evaluation, to produce successful policies in the double cart-pole swing-up task. We experimented with fixing the dropout masks across optimizer iterations, and using CRNs for the particle re-sampling step in Deep-PILCO. Both of these had a noticeable impact on convergence and reduced the computational cost of every policy update. We observed an improvement on the number of trials required for finding successful policies, and a reduction on the final accumulated cost.

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