Off Environment Evaluation Using Convex Risk Minimization

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Abstract—Applying reinforcement learning (RL) methods on robots typically involves training a policy in simulation and deploying it on a robot in the real world. Because of the model mismatch between the real world and the simulator, RL agents deployed in this manner tend to perform suboptimally. To tackle this problem, researchers have developed robust policy learning algorithms that rely on synthetic noise disturbances. However, such methods do not guarantee performance in the target environment. We propose a convex risk minimization algorithm to estimate the model mismatch between the simulator and the target domain using trajectory data from both environments. We show that this estimator can be used along with the simulator to evaluate performance of an RL agent in the target domain, effectively bridging the gap between these two environments. We also show that the convergence rate of our estimator to be of the order of $n^{-1/4}$, where $n$ is the number of training samples. In simulation, we demonstrate how our method effectively approximates and evaluates performance on Gridworld, Cartpole, and Reacher environments on a range of policies. We also show that the our method is able to estimate performance of a 7 DOF robotic arm using the simulator and remotely collected data from the robot in the real world.

I. INTRODUCTION

Reinforcement learning (RL) has demonstrated success in a wide variety of applications such as AlphaGo [1], recommender systems [2], and robotics [3], [4], [5], [6], albeit with some concerns regarding their sensitivity to hyperparameters [7]. Using such hyperparameter sensitive algorithms might lead to an RL agent learning sub-optimal policies, which gets further exacerbated when there is a mismatch between the training environment and the intended target environment.

A typical approach to robot learning involves training and optimization of policy in a software based simulator of the same robot [8], [9]. A robot trained in such a manner tends to perform sub-optimally in the intended target environment [10]. The primary reason behind this sub-optimal performance that these simulators fail to capture the nuances and the real world environment accurately, which is often referred to as the Sim2Real gap [11]. These nuances either require strong assumptions (e.g., modelling contact forces) or are extremely difficult to model (e.g., human-robot interaction). The resulting sub-optimality is not only hard to characterize but it also might lead to potentially hazardous scenarios in high risk environments [12].

To account for such model mismatches, Robust RL algorithms learn a policy which is robust to synthetic perturbations in the simulator [13], [14]. These synthetic perturbations are created under the assumption that the discrepancy between the simulator and the target domain is due to an misidentification of simulator parameters. These simulators are often governed by a model with a lower complexity than the one in the target domain or struggle to capture real-world disturbances [15]. Applying robust RL techniques to account for significant modeling error or higher complexity altogether will likely not be enough to ensure a successful domain transfer without extensive real world validation [16]. We believe that one of the reasons such policies fail to work in practice is due to a fundamental misunderstanding and lack of formalism of model mismatch and policy evaluation across model or environment changes. For example, using robot learning to manipulate and solve a Rubik’s cube required more than two years of research on developing a state-of-the-art robust learning algorithms as compared to six months it took them to learn the same task in simulation [17].

We begin our work with an assumption that it is possible to collect data of agent behaviors from the target environment. In this paper, we use a small amount of data from the target domain to learn a mismatch function that modifies simulator performance to be more reflective of true performance in deployment. We quantify this mismatch function as the as a transition ratio estimation problem between the simulator and the target domain, both of which are modelled as Markov Decision Processes (MDP). In order to estimate this transition ratio, we further pose this estimation as an optimizer of a convex risk minimization algorithm that utilizes trajectory samples from both the target and the simulator environments. We then use this estimated ratio along with the simulator to evaluate a robot agent’s performance in the target domain.

We demonstrate that our estimator tends to approximate the true transition ratio with the accuracy error decreasing with the rate of $n^{-1/4}$, where $n$ is the number of transition samples used to estimate the ratio. We also illustrate the effectiveness of our algorithm to approximate the returns for a short time horizon by proving an exponential dependence of our estimator on the time horizon.

We present the following contributions: (1) We introduce off-environment evaluation, which learns to incorporate model mismatch into the evaluation of a fixed policy across different environments; (2) We use results from convex risk minimization to efficiently learn the model mismatch as the ratio of transition probabilities across two environments; (3) Using tools from statistical learning theory, we bound the error rate of our estimator as a function of the number of samples from the target domain; and (4) We demonstrate the utility of our approach on three task settings, a large discrete example (gridworld), and continuous environments (cartpole, reacher and kinova).
This paper is organized as follows. Section II reviews relevant literature. Section III introduces necessary preliminaries to pose our problem. Section IV discusses our proposed method of off-environment policy evaluation. Section V proves the theoretical error bounds of our algorithm. We demonstrate our results by starting with a discrete-state, discrete-action MDP and building up to a real robot manipulator in Section VI and conclude our paper in Section VII.

II. RELATED WORK

In this section, we review relevant literature that considers model mismatch, covariate shift, and off-policy evaluation which inspired our formulation of off-environment evaluation.

A. Model Mismatch and Covariate Shift

Model mismatch between two domains is well studied in machine learning, often in context of estimating covariate shift [18], [19]. Covariate shift occurs when the training and the test data are sampled from different distributions. The goal of the above work is to learn a classifier that generalizes well on the test distribution while being learned entirely on the training dataset.

The impact of covariate shift is often mitigated by estimating the distributional mismatch factor between the training and the testing distributions \( \beta(x) \) [20]. The factor is then used to re-weight samples on the training dataset such that higher weights are assigned to data points which have a higher likelihood of being in the test distribution than the training distribution. Our work extends this idea of using a distributional mismatch factor to estimate mismatch between two Markov Decision Processes (MDP), not just distributions.

B. Off-Policy Evaluation

Approximating performance by a target policy given access to data from a different behavior policy falls under the class of Off Policy Evaluation (OPE) in reinforcement learning [21]. OPE literature is generally divided into three class of methods, inverse propensity scoring [22], [23], direct methods [24], [25], and hybrid methods [26], [27].

We are inspired by a subset of direct methods that aims to minimize a convex risk criteria to estimate the average state-action density ratios between the behavior and the target policy based on the data from behavior policy and the functional form of target policy returns [28]. The density ratio is later used to re-weight the reward function to estimate returns using data available from the behavior policy. Similar to the direct set of methods, our work takes advantage of a convex risk minimization algorithm to estimate density ratios between the data but unlike these set of methods we use convex risk minimization to estimate the transition ratio between two different MDP environments.

III. PRELIMINARIES

In this section, we introduce our notation for MDPs and reinforcement learning and present the preliminaries for importance sampling and the associated estimators.

A. MDPs and Reinforcement Learning

RL problems are modelled as a Markov Decision Process (MDP), which are represented as a 5-tuple \( M = \langle S, A, P, r, S_0 \rangle \), where \( S \) is the state space, \( A \) is the set of available actions to the agent, \( P \) gives us the underlying transition probability of the next state given the current state and action taken in the environment, and \( S_0 \) is the distribution from which initial states \( s_0 \) are sampled. We define a stationary policy \( \pi : S \to \Delta(A) \) as a probability distribution over actions for each state.

At every time step \( t \), the environment evolves to state \( s_{t+1} \sim P(\cdot|s_t, a_t) \) from state \( s_t \) by taking an action \( a_t \) according to a policy \( \pi(\cdot|s_t) \). We define value of a policy by the function \( J(\pi) \) which calculates the average cumulative discounted sum of rewards \( r : S \times A \to \mathbb{R} \) over an infinite time horizon:

\[
J(\pi) = E \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right]
\]

where \( \gamma \in (0, 1] \) is the discount factor. An alternative formulation to calculate \( J(\pi) = \frac{1}{1-\gamma} E_{(s,a) \sim P}[r(s,a)] \) involves calculating expectation under the distribution \( d_P(s,a) \), which is the normalized discounted stationary distribution:

\[
d_P(s,a) = (1-\gamma) \sum_{t=0}^{\infty} \gamma^t P(s_t = s, a_t = a)
\]

Similarly define the normalized discounted state-action-state distribution. We observe that the relationship between \( d_P(s,a) \) and \( d_P(s,a,s') \) can be expressed by:

\[
d_P(s,a,s') = d_P(s,a) P(s'|s,a)
\]

It is worth noting that this relationship becomes necessary to estimate the mismatch between two MDPs. To estimate this mismatch, we first define two MDP environments: training MDP \( M_{tr} \) and testing MDP \( M_{te} \).

\[
M_{tr} = \langle S, A, P_{tr}, r, S_0 \rangle, \quad M_{te} = \langle S, A, P_{te}, r, S_0 \rangle
\]

Note that both these MDPs are identical in all elements except the environment model.

Mathematically, we wish to estimate \( J_{P_{te}}(\pi) \) while having full access to \( M_{tr} \) and limited data from \( M_{te} \). First, we wish to estimate the ratio of transition probability \( \zeta = \frac{P_{tr}(s'|s,a)}{P_{te}(s'|s,a)} \) and use this ratio to estimate \( J_{P_{te}}(\pi) \) using \( M_{tr} \) and concepts from importance sampling.

B. Importance Sampling

Importance sampling is a technique to estimate the statistical properties of a given probability distribution, given access to samples from a similar distribution. Consider two probability distributions on the same sample space \( (\Omega, F, P) \) and \( (\Omega, F, Q) \). We want to infer a statistical property \( E_x P[G(x)] \), for any \( G : \Omega \to \mathbb{R} \), with only access to
samples from $x \sim Q$. Under the assumption that $\forall x \in \Omega$, if $P(x) > 0 \Rightarrow Q(x) > 0$, we can re-write the expectation in the following form:

$$E_{x \sim P}[G(x)] = \sum_{x \in \Omega} P(x)G(x) = E_{x \sim Q}\left[\frac{P(x)}{Q(x)}G(x)\right]$$ (3.5)

The term $\frac{P(x)}{Q(x)}$ is often referred to as the importance sampling factor $\beta(x)$. When using inverse propensity scoring methods for off policy evaluation methods, this ratio $\beta(x)$ is generally known in advance. However, in some applications, this ratio needs to be estimated based on samples from the distribution $x \sim P$ and $x' \sim Q$. In the next section, we discuss about one such method to estimate the ratio $\beta(x)$.

C. Estimating the Importance Sampling Factor

In our approach, we wish to learn $\beta(x)$ as a function of the state space. For that purpose, we look at the entropy regularisation class of methods which re-formulates the divergence between these two distributions in terms of their convex dual [29]. Specifically, the Kullback-Leibler divergence between two distributions $P$ and $Q$ can be rewritten as a maximisation problem over a space of functions $G$:

$$\bar{D}_{KL}(P\|Q) = \max_{g \in \mathcal{G}} \sum_{x' \in \Omega} P(x') \log(g(x')) - \sum_{x \in \Omega} Q(x)g(x) + 1.$$ (3.6)

Note that the optima of the above problem is $g^* \in \mathcal{G} = \frac{P(x)}{Q(x)}$, as desired. In practice, we only have access to $n$ samples each from $P$ and $Q$. Thus, the optimal $g^*$ is approximated by searching for $\hat{g}_n$ that minimizes the empirical loss along with a regularizer $I(g)$ to prevent over-fitting:

$$\hat{g}_n = \arg\min_{g \in \mathcal{G}} \frac{1}{n} \sum_{i=1}^{n} g(x_i') - \frac{1}{n} \sum_{i=1}^{n} \log(g(x_i)) + \frac{\lambda_n}{2} I(g)^2$$ (3.7)

We thus define $\hat{\epsilon}$ as the ratio of conditional probabilities:

$$\hat{\epsilon}(s_k|s_{k-1}, a_{k-1}) = \frac{P_{tr}(s_k|s_{k-1}, a_{k-1})}{P_{tr}(s_k|s_{k-1}, a_{k-1})}$$ (4.3)

Using importance sampling we thus show our methodology that can assess the policy performance in the testing environment using the training environment and the ratio of transition probabilities between two MDPs.

B. Estimating $\hat{\epsilon}$

We showed how a convex risk minimization algorithm can estimate the ratio of two probability distributions. Now, we use these principles to estimate the ratio of two conditional probabilities (i.e., the transition probabilities for environment models). Using the trajectory data collected on the testing MDP, we apply convex risk minimization algorithm previously described. We wish to calculate two types of density ratios: $\frac{dP_{tr}(s,a,s')}{dP_{te}(s,a,s')}$ and $\frac{dP_{te}(s,a)}{dP_{tr}(s,a)}$. We calculate $\hat{\epsilon}$ by calculating the ratio of these two density ratios which follows simply from the relation as mentioned in equation (3.3):

$$\hat{\epsilon}(s'|s,a) = \frac{\left(\frac{dP_{te}(s,a,s')}{dP_{te}(s,a,s')}\right)}{\left(\frac{dP_{tr}(s,a)}{dP_{tr}(s,a)}\right)}$$ (4.4)

Using the $\hat{\epsilon}$ estimator along with equation (4.2), we can now approximate $J_{P_{te}}(\pi)$ using just the training MDP. Note that whenever we use an estimate $\hat{\epsilon}$ to approximate $J_{P_{te}}$, we use the notation $\hat{J}_{P_{te}}$.
V. Error Analysis

To characterize the error of our estimator, we use existing results developed for empirical risk minimization algorithms to upper-bound the error on the KL-divergence. Using first order Taylor expansion, we later use that upper-bound the error in estimating $\zeta$. We also use this estimator error to approximate the upper-bounds in evaluating $J_{P_{te}}(\pi)$ using the training environment.

A. Estimation Error

Before analysing estimator error, we make the following assumptions.

Assumption 5.1: For any $g \in \mathcal{G}$, we assume that $\nu \leq g(x) \leq \mu$ \forall $x \in \Omega$. Note that $\nu < 1$ and $\mu > 1$

Note that estimating $\zeta$ (equation 4.3) requires calculating a ratio of two entities. The lower bound assumption is to make sure we do not run into numerical issues.

Assumption 5.2: $\exists g^* \in \mathcal{G}$ such that $g^*(x) = \frac{p(x)}{q(x)}$

For the sake of simplicity, we will also assume that the optimizer contains the true minimizer $g^*$. Under these assumptions, we analyse the error between the empirically estimated optimizer $\hat{g}_n$ and the true estimator $g^*$.

Theorem 5.1: Under assumption 5.1, we can upper bound the estimator error between $\hat{g}_n$ and $g^*$, with probability at-least $1 - \delta$ for a sufficiently large $n$ by:

$$\|\hat{g}_n - g^*\|_\infty^2 \leq K e^{D_\infty(P \| Q)} \left( \sqrt{\frac{1}{n}(\mu + \max(\log \mu, -\log \nu))} + \frac{2 \log \frac{1}{\delta}}{n} \right)$$ (5.1)

For the sake of simplicity, we denote the upper-bound as a function of the function class $\mathcal{G}$ and $\delta$ as $M(\mathcal{G}, \delta)$. The detailed proofs along with additional experiments can be found in the supplementary material[1]. We observe that the error decreases at the rate of $O(n^{-\frac{1}{2}})$ and scales exponentially with the $\infty$-renyi divergence. Note that in theorem 5.1 we bounded the error in estimating $\zeta$.

Using this estimator error, we now upper-bound the error in estimating $\zeta_n$.

Lemma 5.1: Applying theorem 5.1 we can bound estimation error for $\zeta_n$ as follows:

$$\|\hat{\zeta}_n - \zeta^*\| \leq \frac{\mu(1 + \nu \mu)}{\nu^2} M(\mathcal{G}, \delta) n^{1/4}$$ (5.2)

Theorem 5.2: Under assumptions 5.2 and 5.1 and the assumption that the reward function is bounded by a constant $\|r(s, a)\|_\infty \leq R$, we can bound the error in performance predicted by our algorithm $J_{P_{te}}(\pi)$ for a time horizon $T$ by the following expression:

$$\|J_{P_{te}}(\pi) - J_{P_{te}}(\pi)\|_\infty^2 \leq T M(\mathcal{G}, \delta)^2 R^2 \gamma \left( 1 - (T + 1)\frac{\gamma T}{1 - \frac{\gamma}{2}} + T^2\frac{\gamma T + 1}{(1 - \frac{\gamma}{2})^2} \right)$$ (5.3)

with probability at-least $1 - \delta$.

We observe that although the bound above converges at the rate of $n^{-1/2}$, the bound also has an exponential dependence on the time horizon. Interestingly, the variance for inverse propensity scoring also depends exponentially on time horizon [21]. To reduce the error in practice, we employ to shorter time horizons $T \simeq 100$.

Algorithm 1 Off Environment Evaluation

Given: $d_{P_{te}}, d_{P_{tr}}$

Initialize: $\{g_{\theta_{sa}}, g_{\theta_{a}}\}$

For $t = 1, ..., numIterations$ do:

1: Sample N transitions: $(s_t, a_t) \sim d_{P_{te}}, (s'_t, a'_t) \sim d_{P_{tr}}$

2: $\theta_{sa} = \theta_{sa} - \eta \nabla g_{\theta_{sa}}(g_{\theta_{sa}})$ (equation 5.7)

3: Sample N transitions: $(s_t, a_t, s_{t+1}) \sim d_{P_{te}}, (s_t', a_t', s_{t'+1}) \sim d_{P_{tr}}$

4: $\theta_{sas} = \theta_{sas} - \eta \nabla g_{\theta_{sas}}(g_{\theta_{sas}})$ (equation 5.7)

End For:

Return: $\{\theta_{sa}, \theta_{sas}\}$

VI. EXPERIMENTS AND RESULTS

Our experiments are guided by the following questions:

1. How well does the ratio of two estimated importance sampling (equation 4.3) factors work to estimate conditional probabilities?
2. Can we use our estimator to validate performance?
3. What is the quality of this validation?

3) Can our estimator be applied to real world robots?

We report the average performance by training 10 of these networks, all of which are initialized with different random seeds. Our algorithm is summarized in algorithm[1].

A. Gridworld

In this experiment, we show that our algorithm is able to approximate the ratio of transition probabilities. We also show that it is also possible to validate the policy performance in the test environment using the simulator and our estimator. To that end, we define Gridworld, as a $n \times n$ sized grid space. The agent starts with a fixed initial state at the bottom left corner of the grid and can take one of the four actions {N, S, E, W}. The MDP is designed such that whenever the agent takes an action, (e.g., N) they move in that direction with $1-\varepsilon$ probability and with $\varepsilon$ probability end up in any of the remaining adjacent states. An episode ends when the agent reaches the goal state in the top-right corner of the grid.

We use Gridworld with $\varepsilon = 0.3$ as the training MDP and Gridworld with $\varepsilon = 0.1$ as the testing MDP. In figure 1(a) we plot the mean absolute error of the transition probabilities over all the state-action-state pairs along with one standard deviation. The absolute error is plotted against the sample
we notice that the importance sampling method performs
value of these transition probabilities, so the only error 
that arises in the evaluation is the error due to averaging 
over finite number of samples. We also compare our 
estimation error against different grid sizes \{10 \times 
10, 20 \times 20, 40 \times 40\}. We observe that the estimation error 
decreases with sample size, while larger grids require more 
samples to achieve reasonable error margins. These results 
highlight the dependence of the estimator on the size of the 
state space and the need for more samples in more complex 
environments.

Next, we evaluate the performance of a policy using the 
training environment and the estimated transition probabi 
lity. The oracle is the estimator that knows the true 
performance over a range of policies in the target 
environment. We observe that as divergence between 
true performance over a range of policies in the target 
environment data, tends to perform worse.

In each of these figures, we compare our performance 
against the true value which is the actual performance in the 
test environment, the oracle, and the importance sampling 
estimator. The oracle is the estimator that knows the true 
value of these transition probabilities, so the only error 
that arises in the evaluation is the error due to averaging 
over finite number of samples. We also compare our method 
against the importance sampling (IS) estimator. IS estimators 
trace their origins from Off Policy Evaluation methods where 
we have data from a behavior policy and we wish to evaluate 
performance for a given target policy. In all of these figures, 
we notice that the importance sampling method performs 
better whenever the target policy is close to behavior policy, 
the performance deteriorates as target policy moves away 
from the behavior policy. We observe that our method tends 
to generalize well over a range of different policies.

It is important to note that the best performance that our 
estimator can ideally get is the one approximated by the 
oracle. One might notice here that our estimator tends to 
perform better than the oracle. A possible reason could be 
that, while optimizing, we never constrain the neural network 
to learn over the structure of the ratio of two probability 
distributions. For example, suppose the function \( \hat{\beta} \in \mathcal{G} \) is 
the optimum function that maximizes equation \ref{eq:beta}. On top of 
optimizing the equation, \( \hat{\beta} \) also needs to satisfy the constraint 
\[ \sum_x \hat{\beta}(x)q(x) = 1. \]

We assume that this constraint will be implicitly satisfied 
while optimizing, but since the algorithm empirical samples 
from distributions to calculate \( \hat{\beta} \), it may not satisfy the above 
constraint.

B. Cartpole Environment

We now examine the Cartpole environment, which has a 
continuous state space and discrete action space. Since the 
Carpole environment is a highly unstable environments, good 
sampling strategies are very important, as the estimator tends 
to fail to generalize if only poor data is collected. For the 
Cartpole environment, the training MDP has gravity \( g = 10.0m/s^2 \). We evaluate our performance on a range of test 
MDPs with gravity \( g = \{7.5, 10.0, 12.5, 15.0\}m/s^2 \). As in 
the gridworld environment, we demonstrate our performance 
over a range of policies parameterized by \( \delta, \pi_{\delta}(\cdot|s) = \delta \cdot 
U(\{|A|\}) + (1-\delta) \cdot \pi_E(\cdot|s) \). The expert policy is a deterministic 
policy trained using the cross entropy method \cite{31}. We plot 
our results for each of the target environments in figure \ref{fig:cartpole} 
over 100 timesteps. We compare our results against a model 
based baseline which learns the model using the same data 
that was used to learn the transition ratio. We also use an IS 
based OPE as a baseline to compare performance.

We observe that our algorithm closely approximates the 
true performance over a range of policies in the target 
environment. We also observe that as divergence between 
the two environments increases, the performance predicted 
by our algorithm tends to deteriorate. In comparison, the im-
portance sampling baseline works only well when the target 
policies near the data collection policy but the performance 
soon deteriorates after that. On the other hand, the MLE 
which learns the model of the environment using the target 
environment data, tends to perform worse.

C. Reacher Environment

We also evaluate our performance on a continuous state, 
continuous action Reacher Environment. For these exper-
iments pertaining to the Reacher environment, the training 
environment has both link lengths set to 0.1m. We validate 
the performance of our algorithm on a set of two test 
environments. The first target environment has twice the 
length of the link as the training environment. The second
We evaluate the performance of a deployed agent using a minimal amount of data in the target environment along with access to the training environment. We first estimate the transition probability ratio between two MDPs using convex risk minimization algorithm. We demonstrate that this ratio can be used to measure performance of an RL policy in the target environment using the training environment and the estimator.

Our experiments demonstrate that, using data from the real world which combined with the simulator, one can indeed approximate performance of any policy. We believe that the ability to validate performance of agents in another environment can further help us learn policies in the training environment that are well performing in the target domain. However, we note that the quality of data collected over target environment does impact performance. It was observed that data collected using a sub-optimal policy tends to generalize well. While we demonstrated our method on standard simulators plus real world robot, exploring the utility of such methods on more complex systems will be explored in future work.

VII. Conclusion and Remarks

In this paper, we propose an algorithm that can evaluate performance of a deployed agent using a minimal amount of data in the target environment along with access to the training environment. We first estimate the transition probability ratio between two MDPs using convex risk minimization algorithm. We demonstrate that this ratio can be used to measure performance of an RL policy in the target environment using the training environment and the estimator.

To demonstrate the practicality of our algorithm in a real world setting Sim2Real tasks, we evaluate the performance of our algorithm on Kinova Gen3 modular robotic arm. We use a Kinova simulator that was designed for training RL algorithms [32]. Using this simulator along with demonstration data collected on the Robot, we optimize equation 3.7 calculate the ratio of transition probabilities.

Using this estimated conditional probability we evaluate the performance of a proportional controller that maneuvers the robot arm from an initial point to a final goal state. To that end, we choose 5 different goal states and the cost function incurred at each of the goal states is averaged over 10 runs each. We compare the performance against the one predicted by our algorithm using the simulator and the estimated conditional probability over 50 trajectories. In addition, we also report the returns approximated by the simulator. All of these results are tabulated in Table I.

We observe that the performance of the simulator as compared to the one observed on the robot is off by around 30%. Using our approach we are able to decrease that discrepancy to around 20%. It is important to read these results in context. We note performance improvement is important because it decreases the Sim2Real gap, which helps us learn policies that are optimal in the target environment.

Fig. 2: Cartpole Environment. Evaluation using our algorithm is depicted in green, MLE baseline is in red, the importance sampling baseline is in blue, and the true performance is in black.

Fig. 3: Reacher Environment. Evaluation using our algorithm is depicted in green, the simulator performance in red, the MLE baseline is in blue, and the true value is in black.

### Table I: Performance as predicted on a Kinova Robot

| Algorithm   | Mean   | Std    |
|-------------|--------|--------|
| True Value  | -0.911 | 0.016  |
| OEE         | -1.095 | 0.101  |
| Simulator   | -1.181 | 0.170  |

We note performance improvement is important because it decreases the Sim2Real gap, which helps us learn policies that are optimal in the target environment.
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