MULTIPOLAR: MULTI-SOURCE POLICY AGGREGATION FOR TRANSFER REINFORCEMENT LEARNING BETWEEN DIVERSE ENVIRONMENTAL DYNAMICS

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ABSTRACT

This work explores a new challenge in transfer reinforcement learning (RL), where only a set of source policies collected under diverse unknown dynamics is available for quickly learning a target task. To address this problem, we propose MULTI-source POLicy AggRegation (MULTIPOLAR), which comprises two key techniques. 1) Learning to aggregate the actions provided by the source policies adaptively to maximize the target task performance. 2) Learning an auxiliary network that predicts residuals around the aggregated actions, which ensures the target policy’s expressiveness even when some of the source policies perform poorly.

We confirmed the significant effectiveness of MULTIPOLAR across six simulated environments ranging from classic control problems to challenging robotics simulations, under both continuous and discrete action spaces. The videos and code are available on the project webpage: https://yonetaniryo.github.io/multipolar/.

1 INTRODUCTION

We envision a future scenario where a variety of robotic systems, which are each trained or manually engineered to solve a similar task, provide their policies for a new robot to learn a relevant task quickly. For example, imagine various pick-and-place robots working in factories all over the world. Depending on the manufacturer, these robots will differ in their kinematics (e.g., link length, joint orientation) and dynamics (e.g., link mass, joint damping, friction, inertia). They could provide their policies to a new robot (Devin et al., 2017), even though their dynamics factors, on which the policies are implicitly conditioned, are not typically available (Chen et al., 2018). Moreover, we cannot rely on a history of their individual experiences, as they may be unavailable due to a lack of communication between factories or prohibitively large dataset sizes. In such scenarios, a key technique to develop would be the ability to transfer knowledge from a collection of robots to a new robot quickly only by exploiting their policies while being agnostic to their different kinematics and dynamics, rather than collecting a vast amount of samples to train the new robot from scratch.

The scenario illustrated above poses a new challenge in the transfer learning for reinforcement learning (RL) domains. Formally, consider multiple instances of a single environment with diverse state transition dynamics, e.g., independent robots presented in Figure 1 (left), which reach different states by executing the same actions due to the differences in their kinematics and dynamics designs. Some source agents interacting with one of the environment instances provide their deterministic policy to a new target agent in another environment instance. Then, our problem is: can we efficiently learn the policy of a target agent given only the collection of source policies? Note that information about source environmental dynamics, such as the exact state transition distributions and the history of environmental states, is not visible to the target agent. Also, the source policies are neither trained nor hand-engineered for the target environment instance, and therefore not guaranteed to work optimally and may even fail (Chen et al., 2018). Importantly, these conditions prevent us from adopting existing work on transfer RL between different environmental dynamics, as they require access to source environment instances or their dynamics for training a target policy (e.g., Chen et al. (2018);
Yu et al. (2019); Tirinzoni et al. (2018)). Similarly, meta-learning approaches (Vanschoren, 2018) cannot be used here because they typically train an agent on a diverse set of tasks (i.e., environment instances). Also, existing techniques that utilize a collection of source policies, e.g., policy reuse frameworks (Rosman et al., 2016; Zheng et al., 2018) and option frameworks (Sutton et al., 1999; Bacon et al., 2017; Mankowitz et al., 2018), are not a promising solution because, to our knowledge, they assume source tasks to have the same environmental dynamics but have different goals.

As a solution to the problem, we propose a new transfer RL approach named MULTI-source POLicy AggRegation (MULTIPOLAR). As shown in Figure 1 (right), our key idea is twofold: 1) In a target policy, we adaptively aggregate the deterministic actions produced by a collection of source policies. By learning aggregation parameters to maximize the expected return at a target environment instance, we can better adapt the aggregated actions to unseen environmental dynamics of the target instance without knowing source environmental dynamics nor source policy performances. 2) We also train an auxiliary network that predicts a residual around the aggregated actions, which is crucial for ensuring the expressiveness of the target policy even when some source policies are not useful. As another advantage, MULTIPOLAR can be used for both continuous and discrete action spaces with few modifications while allowing a target policy to be trained in a principled fashion. In our extensive experimental evaluation, we demonstrated the effectiveness of MULTIPOLAR in a variety of environments ranging from classic control problems to challenging robotics simulations.

2 MULTI-SOURCE POLICY AGGREGATION

Problem setting. We formulate our problem under the standard RL framework (Sutton & Barto, 1998), where an agent interacts with its environment modeled by a Markov decision process (MDP). An MDP is represented by the tuple $\mathcal{M} = (\rho_0, \gamma, S, A, R, T)$ where $\rho_0$ is the initial state distribution and $\gamma$ is a discount factor. At each timestep $t$, given the current state $s_t \in S$, the agent executes an action $a_t \in A$ based on its policy $\pi(a_t | s_t; \theta)$ parameterized by $\theta$. Importantly, in this work, we consider both cases of continuous and discrete for action space $A$. The environment returns a reward $R(s_t, a_t) \in \mathbb{R}$ and transitions to the next state $s_{t+1}$ based on the state transition distribution $T(s_{t+1} | s_t, a_t)$. Similar to some prior works on transfer RL (Song et al., 2016; Tirinzoni et al., 2018; Yu et al., 2019), we consider $K$ instances of the same environment which differ only in their state transition dynamics. Namely, we model each environment instance by an indexed MDP: $\mathcal{M}_i = (\rho_0, \gamma, S, A, R, T_i)$ where no two state transition distributions $T_i, T_j; i \neq j$ are identical. Unlike the prior works, we assume that each $T_i$ is unknown when training a target policy, i.e., agents cannot access the exact form of $T_i$ nor a collection of states sampled from $T_i$. For each of the $K$ environment instances, we are given a deterministic source policy $\mu_i : S \rightarrow A$ that only maps states to actions. Each source policy $\mu_i$ can be either parameterized (e.g., learned by interacting with its environment instance $\mathcal{M}_i$) or non-parameterized (e.g., heuristically designed by humans). Either way, we assume that no prior knowledge about the source policies is available for a target agent, such as their representations or original performances, except that they were acquired from a source environment instance $\mathcal{M}_i$ with an unknown $T_i$. This is one of the assumptions that make our problem unique from others, such as policy reuse and option frameworks.

Given the set of source policies $L = \{\mu_1, \ldots, \mu_K\}$, our goal is to train a new target agent’s policy $\pi_{\text{target}}(a_t | s_t; L, \theta)$ in a sample efficient fashion, where the target agent interacts with another environment instance $\mathcal{M}_{\text{target}} = (\rho_0, S, A, R, T_{\text{target}})$ and $T_{\text{target}}$ is not identical to the source $T_i (i = 1, \ldots, K)$ due to their distinct dynamics.
MULTIPOLAR. Here we present the proposed MULTIPOLAR for the continuous action space, and extend it to the discrete space in the appendix. Let us denote by \(a_t^{(i)} = \mu_i(s_t)\) the action predicted deterministically by source policy \(\mu_i\) given the current state \(s_t\). For the continuous action space, \(a_t^{(i)} \in \mathbb{R}^D\) is a \(D\)-dimensional real-valued vector representing \(D\) actions performed jointly in each timestep. For the collection of source policies \(L\), we derive the matrix of their deterministic actions as \(A_t = \left((a_t^{(1)})^\top, \ldots, (a_t^{(K)})^\top\right) \in \mathbb{R}^{K \times D}\). Our key idea is to aggregate \(A_t\) adaptively in an RL loop, i.e., to maximize the expected return. This adaptive aggregation gives us a “baseline” action that could introduce a strong inductive bias in the training of a target policy even without knowing each source environmental dynamics \(T_i\). More specifically, we define the adaptive aggregation function \(F_{agg} : S \rightarrow A\) that produces the baseline action based on the current state \(s_t\) as 
\[
F_{agg}(s_t; L, \theta_{agg}) = \frac{1}{K} \mathbf{1}^K (\theta_{agg} \circ A_t),
\]
where \(\theta_{agg} \in \mathbb{R}^{K \times D}\) is a matrix of trainable parameters, \(\circ\) is the element-wise multiplication, and \(\mathbf{1}^K\) is the all-ones vector of length \(K\). \(\theta_{agg}\) is neither normalized nor regularized, and can therefore scale each action of each policy independently.

Moreover, we learn auxiliary network \(F_{aux} : S \rightarrow A\) jointly with \(F_{agg}\), to predict residuals around the aggregated actions. \(F_{aux}\) is used to improve the target policy training in two ways. 1) If the aggregated actions from \(F_{agg}\) are already useful in the target environment instance, \(F_{aux}\) will correct them for a higher expected return. 2) Otherwise, \(F_{aux}\) learns the target task while leveraging \(F_{agg}\) as a prior to have a guided exploration process. By denoting trainable parameters of \(F_{aux}\) as \(\theta_{aux}\), the MULTIPOLAR function is:
\[
F(s_t; L, \theta_{agg}, \theta_{aux}) = F_{agg}(s_t; L, \theta_{agg}) + F_{aux}(s_t; \theta_{aux}).
\]

Target policy \(\pi_{target}\) can be modeled by reparameterizing the MULTIPOLAR function as a Gaussian distribution \(\mathcal{N}(F(s_t; L, \theta_{agg}, \theta_{aux}); \Sigma)\), where \(\Sigma\) is a covariance matrix estimated based on what the used RL algorithm requires. Since we regard \(\mu_i \in L\) as fixed functions mapping states to actions, this Gaussian policy \(\pi_{target}\) is differentiable with respect to \(\theta_{agg}\) and \(\theta_{aux}\), and hence could be trained with any RL algorithm that explicitly updates policy parameters.

3 EXPERIMENTAL EVALUATION

We aim to empirically demonstrate the sample efficiency of a target policy trained with MULTIPOLAR. To complete the experiments in a reasonable amount of time, we set the number of source policies to \(K = 4\) unless mentioned otherwise. Moreover, we investigate the factors that affect the performance of MULTIPOLAR. To ensure fair comparisons and reproducibility of experiments, we followed the guidelines introduced by Henderson et al. (2018) and François-Lavet et al. (2018) for conducting and evaluating all of our experiments. To show the benefits of leveraging source policies, we compared our MULTIPOLAR policy to the standard multi-layer perceptron (MLP) trained for conducting and evaluating all of our experiments. To show the benefits of leveraging source policies to be policies to be

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Environments. To show the general effectiveness of the MULTIPOLAR policy, we conducted comparative evaluations of MULTIPOLAR in the following six OpenAI Gym environments: Roboschool Hopper, Roboschool Ant, Roboschool InvertedPendulumSwingUp, Acrobat, CartPole, and LunarLander. We chose these six environments because 1) the parameterization of their dynamics and kinematics is flexible enough, 2) they cover discrete action space (Acrobat and CartPole) as well as continuous action space, and 3) they are samples of three distinct categories of OpenAI Gym environments, namely Box2d, Classic Control, and Roboschool. For each of the six environments, we created 100 environment instances with diverse dynamics and kinematics (described in the Appendix B.1), which we used to evaluate MULTIPOLAR.

Results. Figure 2 and Table 1 clearly show that on average, in all the environments, MULTIPOLAR substantially outperformed baseline policies in terms of sample efficiency and sometimes the final episodic reward\(^1\). For example, in Hopper over 2M training samples, MULTIPOLAR with

\(^1\)Episodic rewards in Figure 2 are averaged over 3 random seeds and 3 random source policy sets on 100 environment instances. Table 1 reports the mean of this average over training samples.
Table 1: MULTIPOLAR vs. Baselines. Bootstrap mean and 95% confidence bounds of average episodic rewards over various training samples.

| Methods          | CartPole | LunarLander | Roboschool Hopper | Roboschool Ant | Roboschool InvertedPendulumSwingup |
|------------------|----------|-------------|-------------------|----------------|-----------------------------------|
|                  | 50K      | 200K        | 1M                | 2M             | 1M                               |
| MLP              | 229 (220,237) | 112 (104,121) | 1088 (1030,1146) | 138 (132,143) | 267 (260,273) |
| RPL              | 238 (231,245) | 178 (174,182) | 1120 (1088,1152) | 178 (174,182) | 195 (192,198) |
| MULTIPOLAR       | 252 (245,260) | 181 (177,185) | 1397 (1361,1432) | 138 (132,143) | 476 (456,495) |

We also investigate the effect of source policies performances on MULTIPOLAR sample efficiency in the Hopper environment. Figure 3 in Appendix shows that the source policies were diverse in terms of the performance in their original environment instance. We created two separate pools of source policies, where one contained only high-performing and the other only low-performing ones. Table 2 summarizes the results of sampling source policies from these pools (4 high, 2 high & low, and 4 low performances) and compares them to the original MULTIPOLAR (shown as ‘Random’) also reported in Table 1. Not surprisingly, MULTIPOLAR performed the best when all the source policies were sampled from the high-performance pool. However, we emphasize that such high-quality policies are not always available in practice, due to the variability of how they are learned or hand-crafted under their own environment instance. Finally, Figure 4 in Appendix shows an example where MULTIPOLAR successfully learned to suppress the useless low-performing sources.

Conclusion. We presented a new problem setting of transfer RL, which aims to train a policy efficiently using a collection of source policies acquired under diverse unknown environmental dynamics. Our proposed MULTIPOLAR, achieved a high training sample efficiency in a variety of environments. Future work seeks to involve other types of environmental disparities (e.g., different reward functions and state/action spaces) and to leverage MULTIPOLAR for transferring knowledge in real-world robotics tasks. For further discussions and results, we refer the reader to the Appendix.

*K* = 4 achieved a mean of average episodic reward about three times higher than MLP (i.e., training from scratch) and about twice higher than RPL (i.e., using only a single source policy). It is also noteworthy that MULTIPOLAR had consistently on par or better performance than RPL, which indicates the effectiveness of leveraging multiple source policies.

Here, policies with final episodic reward over 2K are high-performing and below 1K are low-performing.
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Table 3: Sampling range for Ant kinematic and dynamic parameters.

| Kinematics | Links Length Range |
|------------|---------------------|
| Legs       | [0.4, 1.4] × default length |

Dynamics

| Damping     | [0.1, 5] |
|-------------|----------|
| Friction    | [0.4, 2.5] |
| Armature    | [0.25, 3] |
| Links mass  | [0.7, 1.1] × default mass |

Table 4: Sampling range for CartPole kinematic and dynamic parameters.

| Kinematics | Links Length Range (m) |
|------------|-------------------------|
| Pole       | [0.1, 3] |

Dynamics

| Force       | [6, 13] |
|-------------|---------|
| Gravity     | [-14, -6] |
| Poll mass   | [0.1, 3] |
| Cart mass   | [0.3, 4] |

ACKNOWLEDGMENTS

The authors would like to thank Robert Lee, Felix von Drigalski, Yoshihisa Ijiri, Tatsunori Taniai, and Daniel Plop, for the insightful discussions and helpful feedback on the manuscript.

A MULTIPOLAR FOR DISCRETE ACTION SPACES

We can formulate the target policy of MULTIPOLAR in a principled fashion for actions in a discrete space. Specifically, instead of a $D$-dimensional real-valued vector, here we have a $D$-dimensional one-hot vector $a_i(t) \in \{0, 1\}^D$, $\sum_j (a_i(t))_j = 1$ as outputs of $\mu_i$, where $(a_i(t))_j = 1$ indicates that the $j$-th action is to be executed. Following Eq (1), $F(s_t; L, \theta_{agg}, \theta_{aux}) = F_{agg}(s_t; L, \theta_{agg}) + F_{aux}(s_t; \theta_{aux})$, the output of $F(s_t; L, \theta_{agg}, \theta_{aux})$ can be viewed as $D$-dimensional un-normalized action scores, from which we can sample a discrete action after normalizing it by the softmax function.

B EXPERIMENTAL DETAILS

B.1 EXPERIMENTAL PROCEDURE

For each of the six environments, we first created 100 environment instances by randomly sampling the dynamics and kinematics parameters from a specific range shown in Tables 3, 4, 5, 6, 7 and 8. For example, Table 5 provides the sampling ranges for Hopper environment parameters defined similar to Chen et al. (2018). Note that we defined the sampling ranges for each environment such that the resulting environment instances involve significantly different dynamics. Also, these parameters were used only for simulating environment instances and were not available when training a target policy.

Then, for each environment instance, we trained an MLP policy that was used in two ways: a) the baseline MLP policy for each environment instance, and b) one of the 100 members of the source policy candidate pool from which we sample $K$ of them to train MULTIPOLAR policies and one of them to train RPL policies. Specifically, for each environment instance, we trained three MULTIPOLAR and three RPL policies with distinct sets of source policies selected randomly from the candidate pool. The learning procedure explained above was done three times with fixed different random seeds to reduce variance in results due to stochasticity. As a result, for each of the six environments, we had 100 environment instances × 3 random seeds = 300 experiments for MLP and 100 environment instances × 3 choices of source policies × 3 random seeds = 900 experiments for RPL and MULTIPOLAR. The aim of this large number of experiments is to obtain correct insights into the distribution of performances (Henderson et al., 2018). Due to the large number of experiments for all the environments, our detailed analysis and ablation study of MULTIPOLAR

\footnote{Although we used trained MLPs as source policies for reducing experiment times, any type of policies including hand-engineered ones could be used for MULTIPOLAR in principle.}
Table 5: Sampling range for Hopper kinematic and dynamic parameters.

| Links  | Length Range (m) |
|--------|------------------|
| Leg    | [0.35, 0.65]     |
| Foot   | [0.29, 0.49]     |
| Thigh  | [0.35, 0.55]     |
| Torso  | [0.3, 0.5]       |

Table 6: Sampling range for InvertedPendulum-Swingup kinematic and dynamic parameters.

| Links  | Length Range (m) |
|--------|------------------|
| Pole   | [0.2, 2]         |

| Dynamics |
|----------|
| Damping  | [0.1, 5]         |
| Friction | [0.5, 2]         |
| Armature | [0.5, 3]         |
| Gravity  | [-11, -7]        |
| Links mass | [0.4, 3] × default mass |

Table 7: Sampling range for Acrobot kinematic and dynamic parameters.

| Kinematics |
|------------|
| Links      | Length Range (m) |
| Link 1&2   | [0.3, 1.3]       |

| Dynamics |
|----------|
| Links mass | [0.5, 1.5] |
| Links center mass | [0.05, 0.95] × link length |
| Links inertia moments | [0.25, 1.5] |

Table 8: Sampling range for LunarLander kinematic and dynamic parameters.

| Kinematics |
|------------|
| Side engine height | [10, 20] |

| Dynamics |
|----------|
| Scale    | [25, 50] |
| Initial Random | [500, 1500] |
| Main engine power | [10, 40] |
| Side engine power | [0.5, 2] |
| Side engine away | [8, 18] |

components were conducted with only Hopper, as its sophisticated second-order dynamics plays a crucial role in agent performance (Chen et al., 2018).

B.2 Source Policies Histograms

To generate environment instances, we uniformly sampled the dynamics and kinematics parameters from the ranges defined in Section B.1. Figure 3 illustrates the histograms of the final episodic rewards of source policies on the original environment instances in which they were acquired.

C Evaluation Metric

Following the guidelines of (Henderson et al., 2018), to measure sampling efficiency of training policies, i.e., how quick the training progresses, we used the average episodic reward over training samples. Also, to ensure that higher average episodic reward is representative of better performance and to estimate the variation of it, we used the sample bootstrap method to estimate statistically relevant 95% confidence bounds of the results of our experiments. Across all the experiments, we used 10K bootstrap iterations and the pivotal method.

Specifically, we calculated the mean of average episodic rewards in Tables 1, 2, 11, and 12, over a specific number of training samples (the numbers at the header of the tables e.g., 50K and 100K for the CartPole) which we denote by $T$, as follows. For each experiment in an environment instance, we computed the average episodic reward by taking the average of the rewards over all the episodes the agent played from the beginning of the training until collecting $T$ number of training samples. Then we collected the computed average episodic rewards of all the experiments, i.e., all the combinations of three random seeds, three random sets of source policies (for RPL
and MULTIPOLAR), and 100 target environment instances. Finally, we used the sample boot-strap method (Efron & Tibshirani, 1993) to estimate the mean and the 95% confidence bounds of the collected average episodic rewards. We used the Facebook Boostrapped implementation: https://github.com/facebookincubator/bootstrapped.

**D IMPLEMENTATION DETAILS**

All the experiments were done using the Stable Baselines (Hill et al., 2018) implementation of learning algorithms as well as its default hyperparameters and MLP network architecture for each environment. Based on the performance of learning algorithms reported in (Hill et al., 2018), all the policies were trained with Soft Actor-Critic (Haarnoja et al., 2018) in the LunarLander environment and with Proximal Policy Optimization (Schulman et al., 2017) in the rest of the environments. For fair comparisons, in all experiments, auxiliary network $F_{aux}$ had an identical architecture to that of the MLP. Therefore, the only difference between MLP and MULTIPOLAR was the aggregation part $F_{agg}$, which made it possible to evaluate the contribution of transfer learning based on adaptive aggregation of source policies. Also, we avoided any random seed optimization since it has been shown to alter the policies’ performance (Henderson et al., 2018). Note that we did not do any hyperparameter-tuning but followed the default parameters of Hill et al. (2018). We used the Roboschool implementation of Hopper, Ant, and InvertedPendulumSwingup since they are based on an open-source engine, which makes it possible for every researcher to reproduce our experiments. To run our experiments in parallel, we used GNU Parallel tool (Tange, 2018).

Tables 9 and 10 summarize all the hyperparameters used for experiments on each environment. As done by Hill et al. (2018), to have a successful training, rewards and input observations are normalized using their running average and standard deviation for all the environments except CartPole and LunarLander. Also, in all of the experiments, $\theta_{agg}$ is initialized to be the all-ones matrix.

**E ADDITIONAL RESULTS**

**E.1 ABLATION STUDY**

To demonstrate the importance of each component of MULTIPOLAR, we evaluated the following degraded versions: (1) $\theta_{agg}$ fixed to 1, which just averages the deterministic actions from the source policies without adaptive weights (similar to the residual policy learning methods that use raw action outputs of a source policy), and (2) $F_{aux}$ learned independent of $s_t$, which replaces the state-dependent MLP with an adaptive “placeholder” parameter vector making actions a linear combination of source policy outputs. As shown in Table 11, the full version of MULTIPOLAR

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**Figure 3:** Histogram of final episodic rewards obtained by source policies per environment.
Table 9: Hyperparameters for Acrobot, CartPole, Hopper, Ant and InvertedPendulumSwingup.

| PPO Parameters                  | Acrobot | CartPole | Hopper | Ant | InvertedPendulumSwingup |
|---------------------------------|---------|----------|--------|-----|--------------------------|
| #Training samples               | 200K    | 100K     | 2M     | 2M  | 2M                       |
| #Updates per rollout            | 4       | 20       | 10     | 10  | 10                       |
| Learning rate                   | 2.5e-4  | 1e-3     | 2.5e-4 | 2.5e-4 | 2.5e-4                   |
| Mini batch size                 | 8       | 1        | 128    | 32  | 32                       |
| Discount factor                 | 0.99    | 0.98     | 0.99   | 0.99| 0.99                     |
| GAE $\lambda$                  | 0.94    | 0.8      | 0.95   | 0.95| 0.95                     |
| Clip ratio                      | 0.2     | 0.2      | 0.2    | 0.2 | 0.2                      |
| Value function coefficient      | 0.5     | 0.5      | 0.5    | 0.5 | 0.5                      |
| Entropy coefficient             | 0       | 0        | 0      | 0   | 0                        |
| Gradient clipping value         | 0.5     | 0.5      | 0.5    | 0.5 | 0.5                      |
| Optimizer                       | Adam    | Adam     | Adam   | Adam| Adam                     |

MLP & $F_{aux}$ Parameters

| Hidden layers                   | 64-64   | 64-64    | 64-64  | 16  | 64-64                    |
| Activation functions            | tanh    | tanh     | tanh   | tanh| tanh                     |

Table 10: Hyperparameters for LunarLander.

| SAC Parameters                  | LunarLander |
|---------------------------------|-------------|
| #Training samples               | 500K        |
| #Steps before learning starts   | 1K          |
| Buffer size                     | 50K         |
| Learning rate                   | 3e-4        |
| Mini batch size                 | 256         |
| Discount factor                 | 0.99        |
| Soft update coefficient $\tau$  | 5e-3        |
| Entropy coefficient             | learned automatically |
| Model training frequency        | 1           |
| Target network training frequency| 1          |
| #Gradient updates after each step| 1          |
| Probability of taking a random action| 0     |
| Action noise                    | none        |
| Optimizer                       | Adam        |

MLP & $F_{aux}$ Parameters

| Hidden layers                   | 64-64     |
| Activation functions            | relu      |

significantly outperformed the degraded ones, suggesting that adaptive aggregation and predicting residuals are both critical.

E.2 Effect of Number of Source Policies.

Finally, we show how the number of source policies contributes to MULTIPOLAR’s sample efficiency in Table 12. Specifically, we trained MULTIPOLAR policies up to $K = 16$ to study how the mean of average episodic rewards changes. The monotonic performance improvement over $K$ (for $K \leq 16$), is achieved at the cost of increased training and inference time. In practice, we suggest balancing this speed-performance trade-off by using as many source policies as possible before reaching the inference time limit required by the application.
Table 11: Ablation study in Hopper.

| Multi-Polar ($K = 4$) | 1M          | 2M          |
|-----------------------|-------------|-------------|
| Full version          | 138 (132,143) | 283 (273,292) |
| $\theta_{agg}$ fixed to 1 | 118 (111,126) | 237 (222,250) |
| $F_{aux}$ learned independent of $s_t$ | 101 (95,108) | 187 (175,200) |

Table 12: Results with different number of source policies in Hopper.

| Multi-Polar | 1M          | 2M          |
|-------------|-------------|-------------|
| $K = 4$     | 138 (132,143) | 283 (273,292) |
| $K = 8$     | 160 (154,167) | 323 (312,335) |
| $K = 16$    | 177 (172,182) | 357 (348,367) |

E.3 LEARNED AGGREGATION PARAMETERS VISUALIZATION

Figure 4 visualizes an example of how the aggregation parameters $\theta_{agg}$ for the four policies and their three actions were learned during the 2M timestep training of Multi-Polar ($K = 4$) policy in the Hopper environment. In this example, the source policies in the first and second rows were sampled from low-performance pools whereas those in the third and fourth rows were sampled from high-performance pools. It illustrates that Multi-Polar can successfully suppress the two useless low-performing policies as the training progresses.

F RELATED WORK

Transfer between Different Dynamics. Our work is broadly categorized as an instance of transfer RL between different environmental dynamics, in which a policy for a target task is trained using information collected from source tasks. Much related work requires training samples collected from source tasks, which are then used for measuring the similarity between source and target environment instances (Lazaric et al., 2008; Tirinzoni et al., 2018) or for conditioning a target policy to predict actions (Chen et al., 2018). Alternative means to quantify the similarity is to use a full specification of MDPs (Song et al., 2016; Wang et al., 2019) or environmental dynamics (Yu et al., 2019). In contrast, the proposed Multi-Polar allows the knowledge transfer only through the policies acquired from source environment instances with diverse unknown dynamics, which is beneficial when source and target environments are not always connected to exchange information about their dynamics and training samples.

Leveraging Multiple Policies. The idea of utilizing multiple source policies can be found in the literature of policy reuse frameworks (Fernández & Veloso, 2006; Rosman et al., 2016; Li & Zhang, 2018; Zheng et al., 2018; Li et al., 2019). The basic motivation behind these works is to provide “nearly-optimal solutions” (Rosman et al., 2016) for short-duration tasks by reusing one of the source policies, where each source would perform well on environment instances with different rewards (e.g., different goals in maze tasks). In our problem setting, where environmental dynamics behind each source policy are different, reusing a single policy without an adaptation is not the right approach, as described in (Chen et al., 2018) and also demonstrated in our experiment. Another relevant idea is hierarchical RL (Kulkarni et al., 2016; Osa et al., 2019) that involves a hierarchy of policies (or action-value functions) to enable temporal abstraction. In particular, option frameworks (Sutton et al., 1999; Bacon et al., 2017; Mankowitz et al., 2018) make use of a collection of policies as a part of “options”. However, they assumed all the policies in the hierarchy to be learned in a single environment instance. Another relevant work along this line of research is (Frans et al., 2018), which meta-learns a hierarchy of multiple sub-policies by training a master policy over the distribution of tasks. Nevertheless, hierarchical RL approaches are not useful for leveraging multiple source policies each acquired under diverse environmental dynamics.

Learning Residuals in RL. Some recent works adopt residual learning to mitigate the limited performance of hand-engineered policies (Silver et al., 2018; Johannink et al., 2019). We are interested in a more extended scenario where various source policies with unknown performances are
Figure 4: Aggregation parameters $\theta_{agg}$ during the training of MULTIPOLAR ($K = 4$) in the Hopper that has 3-dimensional actions. Here, the first two source policies are low-performing and the last two are high-performing in their original environment instance.

provided instead of a single sub-optimal policy. Also, these approaches focus only on robotic tasks in the continuous action space, while our approach could work on both of continuous and discrete action spaces in a broad range of environments.