Extended Abstract: AutoRL Hyperparameter Landscapes

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This is an Extended Abstract of a Paper accepted for publication at AutoML-Conf 2023.

1 Motivation

As research in RL soars and the field targets increasingly harder learning-based optimization and control problems [21, 23, 3, 2, 10, 5], extracting good performance out of ever more complicated pipelines becomes the need of the hour. Thus, techniques in Automated Reinforcement Learning (AutoRL; [13]) have started to automate the design of RL approaches.

One goal of AutoRL is optimizing hyperparameter configurations that can help an RL agent achieve the best performance. However, the distribution shift from the RL agent generating the learning data through environmental interaction makes it very different from other forms of Machine Learning. Consequently, RL pipelines can be very sensitive to hyperparameter configurations [8, 13], making it difficult to find an optimal static configuration at the beginning of the training, and thus, potentially necessitating adjusting hyperparameters throughout the training process in RL [13].

We develop a novel method to visualize and analyze the performances of different hyperparameter configurations using landscapes. Landscapes, traditionally a part of the optimization community [14, 12], have previously been the subject of analyses for benign characteristics of hyperparameter configurations in supervised learning [17]. To the best of our knowledge, we are the first to bring this to the realm of RL by building a novel pipeline for creating hyperparameter landscapes of dynamic

16th European Workshop on Reinforcement Learning (EWRL 2023).

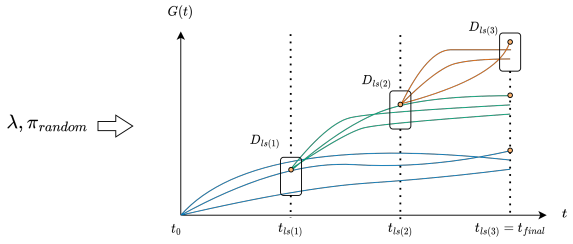


Figure 1: Overview of the data collection process for landscapes with three configurations $\boldsymbol{\lambda}$ and three phases. We initialize the process by training a random RL policy π_{random} on each configuration $\lambda \in \boldsymbol{\lambda}$. The three configurations run till the first landscape point $t_{ls(1)}$ which forms the first landscape dataset $D_{ls(1)}$. The policies are snapshotted at this point, and the policy for the next phase is selected based on the final performance, indicated by the continuation of the blue points. The selected configuration is shown with orange circles. This process is repeated for two more phases to create landscape datasets $D_{ls(1)}$ and $D_{ls(3)}$. The end of the final phase $t_{ls(3)}$ corresponds to the final training point t_{final}

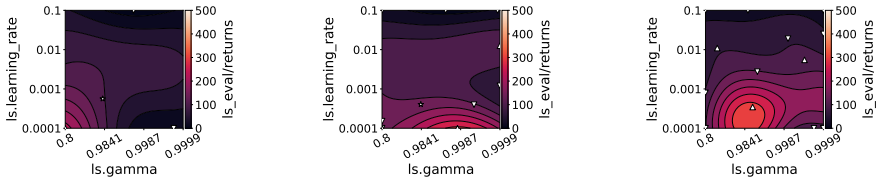
configurations at multiple discrete time steps throughout training. Using the built landscapes, we delineate methods with which the landscapes can be inspected for traits such as their general structure, configuration stability, and hyperparameter importance. Finally, we provide the first empirical evidence supporting the need for dynamic hyperparameter configurations for RL by analyzing the HP landscapes of DQN [21], PPO [19] and SAC [7] on Cartpole, Bipedal Walker and Hopper [4] environments.

2 Building online Hyperparameter Landscapes for Reinforcement Learning

Figure 1 shows an overview of our pipeline for collecting the data to build the landscape. Our approach can be broken down into two steps: Data Collection and Landscape Modeling and Analysis.

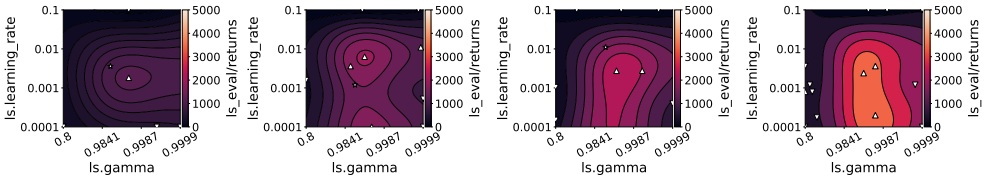
In the data collection phase, we divide the learning timeframe into different phases $0 < t_{ls(1)} < \cdots < t_{final}$, where $t = t_{ls(i)}$ (ls denoting landscape) denotes the time point for collecting landscape data, and $t = t_{final}$ is at the end of training. Each phase entails: (i) using a checkpoint from the last phase to initialize different HP configurations and seed combinations using a scrambled Sobol sampling strategy [22, 9], (ii) running these combinations until the end of the phase, and (iii) determining the fitness of each HP configuration by aggregating the evaluation returns at the end of the phase across the seeds. To determine which configuration should be used as a checkpoint for the next phase, we train the HP configuration until the final timestep t_{final} and use the final performance as an indicator of fitness. To perform the selection, we first choose the configuration set with the highest Interquartile Mean (IQM) in the final phase and initialize this configuration with a seed corresponding to the highest IQM in the selected set. Using IQMs allows us to mitigate the outlier bias prevalent in mean aggregation while incorporating more data in our evaluation than median aggregation [1].

Once the data has been collected, we build the landscapes using Interpolating Landscape Models (ILM), which leverage RBF interpolation with a linear Kernel to construct a continuous surface over the search space from the given samples, and Independent Gaussian Process Regressors (IGPRs), that use the mean of the Gaussian Processes to model the surfaces independently. Based on our experiments, IGPRs provide smoother landscapes that show more global patterns. We additionally use Individual Conditional Expectation (ICE) curves [6] to model one-dimensional slices through the hyperparameter landscape, thus, creating one curve for each hyperparameter connecting the performance to its range. Finally, we perform a modality analysis using the folding test of unimodality [20], where we look at the return distributions to find a pivot point around which the distribution can be folded to reduce the variance. Multi-modal return distributions result in a high variance reduction, while uni-modal ones do not. We use this test to classify the returns into percentages of uni-modality and multi-modality and therefore providing a comment on the stability of the return distribution. Our code can be found here `https://anon-github.automl.cc/r/autorl_landscape-F04D`.



(a) Phase 1 (b) Phase 2 (c) Phase 3

Figure 2: IGPR plots of the mean surfaces for learning rate and discount factor for DQN.



(a) Phase 1 (b) Phase 2 (c) Phase 3 (d) Phase 4

Figure 3: IGPR plots for learning rate and discount factor for SAC across phases

3 Visualizing Landscapes for Inspection

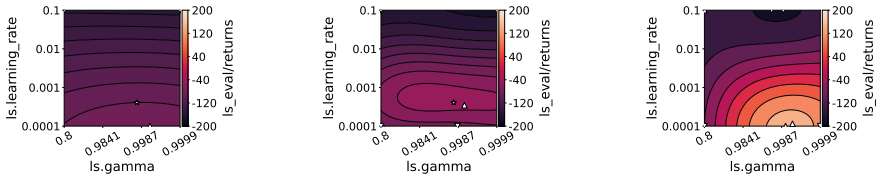
Figure 2, Figure 3, and Figure 4 show the IGPR hyperparameter landscapes of the three agents in our experiments. The local minima are represented by the inverted triangle and the maxima by the normal triangle. The configuration selected for the next stage is represented by a star.

As can be seen, the landscapes strongly vary in their structure over the phases and confirm that the effect of hyperparameters as well as their optimal settings vary throughout training. In this sense, the results promote the use of dynamic configurations, setting a precedent for research on other RL contexts. A deeper look at the plots shows that the performance peaks move strongly for different hyperparameters, indicative of both the environment complexity and optimization procedure.

The performance peak for DQN occurs in a narrow region for both learning rate α and discount factor γ, with γ largely influencing the scores on its own in the final phase. On the other hand, we see a more stable region of peak performance for SAC, potentially indicating better exploration capability of SAC for similar HP ranges. Hence, it requires fewer variations in hyperparameter schedules, which corroborates the advantage of soft updates and entropy-based exploration inherent in SAC. Consequently, potential HP schedules for α and γ would have a greater impact on the learning of TD-based off-policy algorithms such as DQN, something that could be potentially attributed to the learning dynamics of TD-algorithms themselves [11].

For PPO, we see that there is one region with a high performance whose location also changes over the phases. This implies that PPO is less robust to HP decisions in general.

Table 1 presents the overall sizes of the three categories (unimodal, multimodal, and uncategorized). We regard configurations that produce unimodal return distributions to be more stable than those which produce multimodal ones. Generally, more return distributions are categorized as multimodal rather than unimodal. This is especially true for the last phase, where we find 49.22% of configurations to be multimodal for DQN, 60.94% configurations for SAC, and 80.47% for PPO. Although there are some configurations in this area that are classified as unimodal, their return distributions are otherwise not that optimal with their IQMs being dominated by other configurations that are not classified as unimodal. We additionally see that the configurations with unimodal return distributions are almost double for DQN as compared to SAC and PPO, which correlates with the more complicated optimization problem of Hopper and BipedalWalker as compared to CartPole. While further analyses are necessary to ablate the various factors that impact modality, these observations contradict previous observations on benign landscapes of static algorithm configuration and AutoML [15, 17, 18].



(a) Phase 1 (b) Phase 2 (c) Phase 3

Figure 4: IGPR plots of the mean surfaces for learning rate and discount factor for PPO

Category	DQN			SAC				PPO		
	Phase 1	Phase 2	Phase 3	Phase 1	Phase 2	Phase 3	Phase 4	Phase 1	Phase 2	Phase 3
% Unimodal	19.53	13.28	15.62	19.53	09.37	06.25	07.81	12.5	10.94	8.59
% Multimodal	40.63	60.94	60.16	49.22	53.90	57.81	60.94	67.18	60.16	80.47
% Uncategorized	39.84	22.66	22.66	28.90	30.47	24.22	27.34	20.31	28.90	10.94

Table 1: Percentages of configurations assigned to each of the classes from the modality analysis.

4 Concluding Remarks

Our multiphase pipeline for data collection, landscape modeling, and landscape analysis presents a novel way to analyze hyperparameter performances for RL agents across different points of training. Through our experiments, we found drastic changes in the hyperparameter landscape over time for three very different RL algorithms on three diverse environments, suggesting that the use of dynamic configurations in RL may be well-motivated. We additionally showed that the stability of configurations is rather unpredictable depending on a context that is informed jointly by the learning dynamics of the algorithm and the exploration problem. Finally, our modality analysis showed that only a small fraction of hyperparameter configurations with their associated return distributions eventually are unimodal, in contrast to the recent observations of benign landscapes in AutoML and algorithm configuration [16, 17, 18]. This shows that the dynamic configuration of RL agents poses a much harder problem than classical static AutoML addresses so far and calls for new and specialized AutoRL methods. Consequently, our analysis opens up new doors for building more specialized optimizers for RL agents and further research into the interplay between fundamental properties of RL agents such as exploration, credit assignment, and hyperparameter configurations.

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