Contextualize Me – The Case for Context in Reinforcement Learning

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Abstract

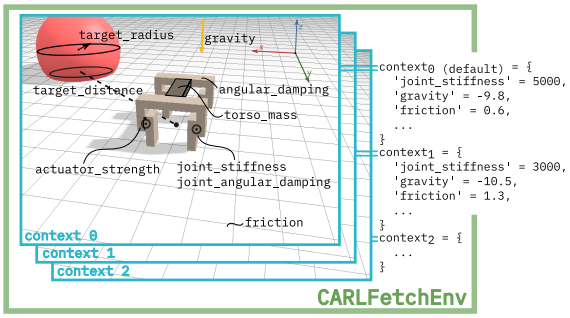
While Reinforcement Learning (RL) has made great strides towards solving increasingly complicated problems, many algorithms are still brittle to even slight environmental changes. Contextual Reinforcement Learning (cRL) provides a framework to model such changes in a principled manner, thereby enabling flexible, precise and interpretable task specification and generation. Therefore cRL formalizes the study of generalization in RL. Our goal is to show how the framework of cRL can contribute to both our theoretical understanding and practical solutions of generalization. We show that theoretically optimal behavior in contextual Markov Decision Processes requires explicit context information. We empirically validate this result on various context-extended versions of common RL environments. They are part of the first benchmark library designed for generalization based on cRL extensions of popular benchmarks, `CARL`, which we propose as a testbed to study general agents further.

1 Introduction

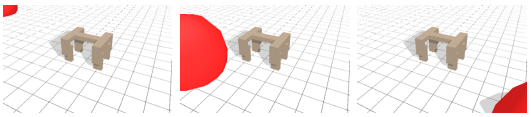
Reinforcement Learning (RL) has shown successes in a variety of domains, including (video-)game playing (Silver et al., 2016; Badia et al., 2020), robot manipulation (Lee et al., 2020a; Ploeger et al., 2020), traffic control (Arel et al., 2010), chemistry (Zhou et al., 2017), logistics (Li et al., 2019) and nuclear fusion (Degrave et al., 2022). At the same time, RL has shown little success in real-world deployments that require generalization. We believe this can largely be explained by the fact that modern RL algorithms are not designed with generalization in mind, making them brittle when faced with even slight variations of their environment (Yu et al., 2019; Meng & Khushi, 2019; Lu et al., 2020).

To address this limitation, recent research has increasingly focused on generalization capabilities of RL agents. Ideally, general agents should be capable of zero-shot transfer to previously unseen environments and robust to changes in the problem setting while interacting with an environment (Ponsen et al., 2009; Henderson et al., 2018; Cobbe et al., 2020; Zhang et al., 2021b; Fu et al., 2021b; Yarats et al., 2021; Abdolshah et al., 2021; Sodhani et al., 2021b; Adriaensen et al., 2022; Kirk et al., 2023). Steps in this direction have been taken by proposing new problem settings where agents can test their transfer performance, e.g. the Arcade Learning Environment's flavors (Machado et al., 2018) or benchmarks utilizing Procedural Content Generation (PCG) to increase task variation, e.g. ProcGen (Cobbe et al., 2020), NetHack (Küttler et al., 2020) or Alchemy (Wang et al., 2021). Furthermore, robustness to distribution shift as well as multi-task learning have been long-standing topics in meta-RL, both in terms of benchmarks (Yu et al., 2019; Sodhani et al., 2021a) and solution methods (Pinto et al., 2017; Finn et al., 2017; Zhu et al., 2020; Zhang et al., 2021d).

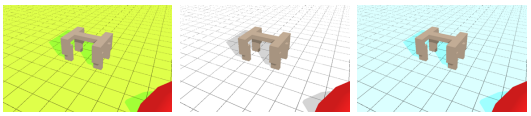
While these extended problem settings in RL have expanded the possibilities for benchmarking agents in diverse environments, the degree of task variation is often either unknown or cannot be controlled precisely. We believe that generalization in RL is held back by these factors, stemming in part from a lack of problem formalization (Kirk et al., 2023). In order to facilitate generalization in RL, cRL proposes to explicitly take environment characteristics, the so called *context* (Hallak et al., 2015), into account. This inclusion enables precise design of train and test distributions with respect to this context. Thus, cRL allows us to reason about which types of generalization abilities RL agents exhibit and to quantify their performance on them. Overall, cRL provides a framework for both theoretical analysis and practical improvements.



(a) Example of a contextual extension of Brax' Fetch (Freeman et al., 2021) as part of CARL



(b) Variations in target distances



(c) Ground friction simulating grass, concrete and ice

Figure 1: CARL allows to configure and modify existing environments through the use of context. This context can be made visible to agents through context features to inform them directly about the current instantiation of the context (see a). Specific instances of CARLFetch with variations in goal distance (see b) and with different ground frictions (grass, concrete and ice, see c).

In order to empirically study cRL, we introduce a benchmark library for Context-Adaptive Reinforcement Learning: CARL. CARL collects well-established environments from the RL community and extends them with the notion of context. To ensure interpretability, CARL considers context which is mainly based on physical properties and thus intuitive to humans. For example, CARL extends Brax (Freeman et al., 2021) environments with properties such as friction, gravity, or the mass of an object (see Figure 1). Through CARL's interface, it is possible to meticulously define the context distributions on which RL agents are trained and evaluated. We use our benchmark library to empirically show how different context variations can significantly increase the difficulty of training RL agents, even in simple environments. We further verify the intuition that allowing RL agents access to context information is beneficial for generalization tasks in theory and practice.

In short, our contributions are: (i) We provide a theoretical and empirical characterization of Contextual Reinforcement Learning (cRL); (ii) We introduce our benchmark library CARL which enables fine-grained context control in benchmarking cRL; and (iii) We demonstrate that context-oblivious agents are not suitable to solve contextual environments on their own.

2 Contextual Markov Decision Processes

In order to facilitate generalization, we first have to rethink how we model the RL problem. While we could follow the common notion of modeling environments as Markov Decision Processes (MDPs), this way of modeling typically assumes a single, clearly defined environment. We believe this problem formulation is overly restrictive. Agents trained under such an assumption fail when the underlying environment does not behave exactly as they have experienced during training. Modeling the problem as a contextual MDP instead (cMDP) (Hallak et al., 2015), we assume that there are multiple related but distinct environments which an agent might interact with and which can be characterized through *context*. This notion of context provides us with the means necessary to study the generalization abilities of RL agents in a principled manner.

What is Context? To help build intuition on what context is and how it might influence the learning problem, we first give an informal treatment of context. In essence, context characterizes how the environment behaves and what its goals look like. In contrast to the observations of an MDP, which describe the changes to the environment step by step, context allows us to reason about how the state will evolve without requiring access to the true transition and reward functions. Further, context features are typically static (i.e., do not change during an episode) or change at a much slower time scale than state observations.

In a robot, for example, joint friction could inform an RL controller how much torque to apply to execute some desired action. In the short horizon, the friction will not change. However, especially if the robot is not well maintained, the friction can increase due to mechanical degradation with the need to adapt accordingly. Context information can now help to appropriately compensate. Another example could be different payloads as context for a robot or different winds for a helicopter (Koppejan & Whiteson, 2009). Note that such a

feature does not need to provide the exact change in transition dynamics, rather it needs to provide a signal of how transition (and reward) functions relate to each other.

Context does not need to influence reward and transition functions at the same time. In goal-based reinforcement learning (e.g., Schaul et al., 2015; Eysenbach et al., 2019), the notion of goals influences the reward function, typically without changing the transition dynamics. For example, an agent needs to traverse an empty gridworld. A goal that is placed to the right of the agent yields high rewards by moving closer. If another goal is now on the left of the agent, the reward for actions switches without changing how the agent traverses the grid (i.e. the transition function).

By its nature, context enables agents to learn more discriminative and thus more general policies. This makes context very well suited to study generalization of RL agents (Kirk et al., 2023). However, context has yet to be widely explored or leveraged in reinforcement learning, and there are many open questions to be addressed. A prominent one among them is how to use context during learning. In the following section, we discuss contextual RL more formally. Later on, we will show how to transform RL methods to make explicit use of contexts to facilitate better generalization.

Contextual Markov Decision Processes (cMDP) (Hallak et al., 2015; Modi et al., 2018; Biedenkapp et al., 2020) allow us to formalize generalization across tasks by extending the standard definition of an MDP in RL. An MDP $M = (\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R}, \rho)$ consists of a state space $\mathcal{S}$, an action space $\mathcal{A}$, transition dynamics $\mathcal{T}$, a reward function $\mathcal{R}$ and a distribution over the initial states ρ. Through the addition of context, we can *define, characterize* and *parameterize* the environment's rules of behavior and therefore induce task *instances* as variations on the problem. In the resulting cMDP, the action space $\mathcal{A}$ and state space $\mathcal{S}$ stay the same; only the transition dynamics $\mathcal{T}_c$, the reward $\mathcal{R}_c$ and the initial state distribution ρ_c change depending on the context $c \in \mathcal{C}$. Through the context-dependent initial state distribution ρ_c, as well as the change in dynamics, the agent may furthermore be exposed to different parts of the state space for different contexts. The context space $\mathcal{C}$ can either be a discrete set of contexts or defined via a context distribution $p_{\mathcal{C}}$. A cMDP $\mathcal{M}$ therefore defines a set of contextual MDPs $\mathcal{M} = \{M_c\}_{c \sim p_{\mathcal{C}}}$.

cMDPs Subsuming Other Notions of Generalization Even though a lot of work in RL makes no explicit assumptions about task variations and thus generalization, there are extensions of the basic MDP models beyond cMDPs that focus on generalization. One of these is *Hidden-Parameter MDPs* (Doshi-Velez & Konidaris, 2016), which allows for changes in dynamics just as in cRL, but keeps the reward function fixed. The reverse is true in goal-based RL (Florensa et al., 2018), where the reward function changes, but the environment dynamics stay the same. *Block MDPs* (Du et al., 2019) are concerned with a different form of generalization than cMDPs altogether; instead of zero-shot policy transfer, they aim at learning representations from large, unstructured observation spaces. An alternative approach is the *epistemic POMDP* (Ghosh et al., 2021) as a special case of a cMDP. Here, transition and reward functions may vary, but the context is assumed to be unobservable. The corresponding approaches then model the uncertainty about which instance of the cMDP the agent is deployed on during test time.

Settings that can be described as a collection of interacting systems, e.g. multi-agent problems, can be formalized as such through *Factored MDPs* (Boutilier et al., 1999; Guestrin et al., 2001). The generalization target here is again not necessarily zero-shot policy transfer, but generalization with respect to one or more of the factored components, e.g. the behavior of a competing agent. Both Block MDPs and Factored MDPs are compatible with cMDPs, i.e., we can construct a Block cMDP or a Factored cMDP in order to focus on multiple dimensions of generalization (Sodhani et al., 2021a).

Apart from these MDP variations, there are also less formalized concepts in RL related to or subsumed by cMDPs. Skill-based learning, for example, relates to cMDPs (da Silva et al., 2012). Some variations of the environment, and therefore areas of the context space, will require different action sequences than others. The past experience of an agent, i.e. its memory, can also be seen as a context, even though it is rarely treated as such. Frame stacking, as is common in e.g. Atari (Bellemare et al., 2016) accomplishes the same thing, implicitly providing context by encoding the environment dynamics through the stacked frames.

Obtaining Context Features Not every task has an easily defined or measurable context that describes the task in detail. Therefore, it is important to examine how context can be obtained in such cases. Often we can

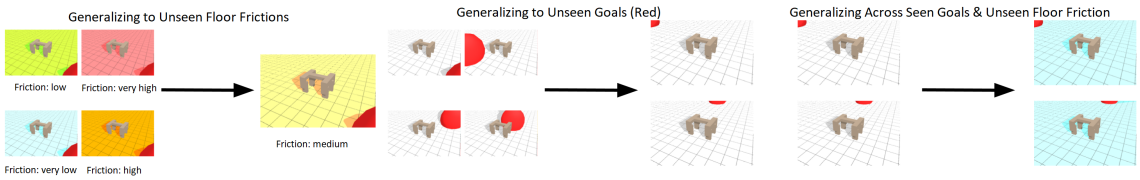


Figure 2: Different train and test relationships result in different generalization tasks: interpolation between known friction levels (left), generalizing to goals further away than seen in training (middle), generalizing to the goal distances in the training distribution with lower friction (right).

only extract very simple context features for a task. For example, even though procedural generation (PCG) based environments do not allow control over the training and test distributions, they can still be considered contextual environments since they are usually seeded. This would give us the random seed as context information (Kirk et al., 2023). However, the seed provides no semantic information about the instance it induces. Obtaining more useful context features should therefore be a focus of cRL. Learned representations provide an opportunity (Jaderberg et al., 2017b; Gelada et al., 2019; Zhang et al., 2021a; Castro et al., 2021) to do this in a data-driven manner. As these representations encode the tasks the agent needs to solve, subspaces of the context space requiring different policies should naturally be represented differently. This idea has previously been applied to detecting context changes in continuous environments (da Silva et al., 2006; Alegre et al., 2021) and finding similar contexts within a training distribution (da Silva et al., 2012). Thus, even without readily available context, representation learning can enable the reliable availability of information relevant for generalization to tasks both in- and out-of-distribution.

3 Reinforcement Learning with Context

In this section, we provide an overview of how context can influence the training of RL agents. We discuss training objectives in the contextual setting and give a theoretical overview of the implications of treating generalization problems that can be modeled as cMDPs like standard MDPs. This should serve as a demonstration of why using the cMDP framework for generalization problems is beneficial and should be explored further. Note that we assume standard cMDPs in this section, meaning the context, if provided to the agent, is fully observable and reflects the true environment behavior.

3.1 Solving cMPDs

Objectives Having defined context and cMDPs, we can now attempt to solve cMDPs. To this end, we must first formulate potential **objectives** being addressed by cRL. In contrast to standard RL, cRL offers several different objectives for the same training setting depending on what kind of generalization we are aiming for. We can provide this objective via a target context distribution that induces the target cMDP $\mathcal{M}$. Depending on the relation between target and training distributions, we can measure interpolation performance, robustness to distribution shift, out-of-distribution generalization, and more, e.g., solving a single expensive hard task by only training on easy ones. Thus, the cRL objective is *defined by the relationship between train and test settings*, similar to supervised learning, but on the level of tasks rather than the level of data points (see Figure 2).

Optimality Regardless of the specific objective, we solve cMDPs in the same way we would solve standard MDPs, though we need to extend the definition of the return. Instead of maximizing the expected reward over time, we use the expected reward over both time and target context distribution. Therefore we define **optimality** in a cMDP in the following way:

Definition 1 *A policy π^* is optimal for a given cMDP $\mathcal{M}$ with target context distribution $p_{\mathcal{C}}$ iff π^* optimally acts on every MDP in $\mathcal{M}$ (i.e. maximizes the return G):*

$$\forall c \sim p_{\mathcal{C}} : \pi^* \in \arg\max_{\pi \in \Pi} \mathbb{E}_{\pi}[G_{c,\pi}]$$

Note that such an optimal policy does not necessarily exist. Malik et al. (2021) showed that the problem of learning a policy π that satisfies Definition 1 may be intractable for some context distributions, even if the contexts are similar.

In order to compare policies across a given target distribution, we propose to compare the gap between optimal and actual performance, what we call the *Optimality Gap* $\mathcal{OG}$. Formally, we define $\mathcal{OG}$ as the gap between the optimal return G_{c,π^*} over the target context distribution c and the return of the given policy π:

$$\mathcal{OG} := \mathbb{E}_{p_c}[G_{c,\pi^*}] - \mathbb{E}_{p_c}[G_{c,\pi}]. \tag{1}$$

In settings where the optimal return is known, we can directly evaluate the optimality gap as the difference between the return of a trained policy and the optimal return. However, in cases where the optimal return is either unknown or intractable, we can instead use an agent trained on each single context as an approximation of the optimal return. However, we have two sources of uncertainty: First, the specialized agent might not reach the best performance achievable in the MDP and second, the uncertainty of the optimal return also depends on the number of context samples for the specialized agent.

3.2 Optimal Policies Require Context

In this section, we give an intuition and a proof sketch of why conditioning the policy not only on the state space $\mathcal{S}$ but also on the context space $\mathcal{C}$ can be beneficial. As a reminder, a standard RL policy is defined as a mapping $\pi : \mathcal{S} \to \mathcal{A}$ from a state observation $s \in \mathcal{S}$ to an action $a \in \mathcal{A}$.[1] In contrast to standard RL, in cRL the state space $\mathcal{S}$ is shared among all MDPs within a cMDP, meaning that states can occur in multiple MDPs even though the transition and reward functions might differ.

3-State cMDP A simple way to exemplify this is through the 3-state cMDP in Figure 3. For the first MDP on the left, the optimal action would be a_0 leading to state S_1 with a high reward of 10. The MDP in the middle is a variation of the same state and action space, where the transition function has changed: while the reward in state S_1 remains 10, action a_0 now leads to state S_2 with a lower reward of 1. Similarly, the MDP on the right is another variation changing the reward function instead of the transition function: a_0 still leads to S_1, but the associated reward now is 1. An agent exposed to such changes would not be able to react appropriately unless the policy is conditioned on the context c_i.

In contrast, a *context-conditioned policy* can distinguish between the contexts and thus receives more guiding feedback during training. Also, it can be more capable to perform optimally at test time given an approximation of the context. We define context-conditioned policies as follows:

Definition 2 *A context-conditioned policy is a mapping $\pi : \mathcal{S} \times \mathcal{C} \to \mathcal{A}$ with state space $\mathcal{S}$, context space $\mathcal{C}$ and action space $\mathcal{A}$.*

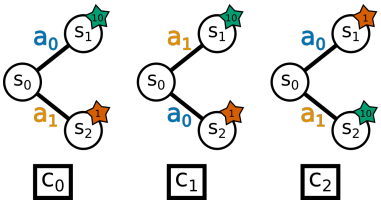


Figure 3: A sample cMDP with three contexts. The original one (left), one changing the transition function (middle) and another the reward function (right).

In order to formalize this intuitive explanation of why context is helpful in generalization, let us first recall what optimal performance means in cMDPs. Definition 1 requires that there exists a policy π^* that is optimal on every context. We will now show that optimal context-oblivious policies like this do not exist in general, but that to obtain optimality, the policy needs to have access to the context.

Proposition 1 *For a given cMDP $\mathcal{M} = \{M_{c_1}, M_{c_2}\}$ defined over two possible contexts c_1 and c_2, there is either a common (context-oblivious) optimal policy π^* for both contexts or there is at least one conflict state s' at which the optimal policy differs between the contexts.*

Proof Sketch Let us look at a given state $s \in \mathcal{S}$ that is reachable in M_{c_1}. Further, let us assume $\pi^*_{c_1}$ is the optimal policy for M_{c_1} that is defined only on states reachable in M_{c_1}. We have to consider the following

[1] Alternatively, one can also define a policy as a probability distribution P(a|s) over the actions given a state. The following line of arguments also holds for stochastic policies but we only outline it for deterministic policies to not clutter notation.

three possible cases for each state $s \in \mathcal{S}$: (i) s is reachable in M_{c_2} and $\pi^*_{c_1}(s)$ is not optimal on M_{c_2}; (ii) s is reachable in M_{c_2} and $\pi^*_{c_1}(s)$ is optimal on M_{c_2}; (iii) s is not reachable in M_{c_2}. We assume that we act within one MDP.

If (i) is true for at least one state $s \in \mathcal{S}$, the optimal policy obviously is different between the contexts in this state, and therefore we have found a conflict state s'. The other two cases do not produce such a conflict. We can, however, construct a policy π^* that is optimal on M_{c_1} and M_{c_2} from $\pi^*_{c_1}$ if for all $s \in \mathcal{S}$ either (ii) or (iii) is true. For any state s where (ii) holds, we simply set $\pi^*(s) = \pi^*_{c_1}(s)$. For states s that are not reachable in M_{c_1} as stated in (iii), $\pi^*_{c_1}$ is not defined. We can therefore extend π^* by these states without changing its optimality on M_{c_1}. Let a^* be the optimal action in such s on M_{c_2}. Then, we define $\pi^*(s) = a^*$. By construction, π^* is then optimal on all states $s \in \mathcal{S}$, and it exists iff there is no state reachable in both contexts where the optimal action for M_{c_1} differs from the one for M_{c_2}. ■

Theorem 1 *An optimal policy π^* for any given cMDP $\mathcal{M}$ is only guaranteed to exist if it is conditioned on the context: $\pi : \mathcal{S} \times \mathcal{C} \to \mathcal{A}$.*

Proof Sketch Let us assume we know an optimal policy π^*_c for any context $c \in \mathcal{C}$. As c induces an MDP and with it a corresponding optimal policy, we know that π^*_c exists. Furthermore, let the sets of optimal policies between at least two MDPs M_{c_1} and M_{c_2} be disjoint. This means no policy exists that is optimal on both c_1 and c_2.

Now let us examine the optimal policy π^* and assume that it exists for this cMDP $\mathcal{M}$. By definition, π^* is optimal on c_1 and c_2. If it is *only* conditioned on the state, $\pi^*(s)$ results in the same action independent of the context. Because the sets of optimal policies for c_1 and c_2 are disjoint, there must be at least one state s', where $\pi^*_{c_1}(s') \neq \pi^*_{c_2}(s')$ according to Proposition 1. As both are optimal in their respective contexts but not in the other and do not result in the same action for s, π^* cannot actually be optimal for both c_1 and c_2. Thus, the optimal policy π^* does not exist. On the other hand, if we can condition the policy on the context, such that $\pi : \mathcal{S} \times \mathcal{C} \to \mathcal{A}$, we can circumvent this problem (for a discussion on how this relates to partial observability, see Appendix A). $\pi^*(s, c) = \pi^*_c$ is optimal for each context. ■

Discussion Theorem 1 raises the question of how performance changes if the policy is *not* conditioned on the context. Apart from the fact that we can construct cMDPs where a policy not conditioned on the context may perform arbitrarily poorly, we intuitively assume the optimality gap should grow the broader $p_\mathcal{C}$ becomes and the more impact slight changes in c have on the transitions and rewards. Formally assessing the optimality gap $\mathcal{OG}$ is another challenge in itself. Another question is how relevant the assumption of disjoint sets of optimal policies for different contexts is in practice. For the case where the observations implicitly encode the context, a single policy can solve different contexts optimally by never entering the conflict above. Assuming this is how generalization is commonly handled in RL. However, we deem this not to be a reliable mechanism to avoid conflicts between context-optimal policies on the same observations. In conclusion, depending on the environment and on how context reflects on the observations, it might be beneficial to explicitly include context, especially on harder and more abstract generalization tasks.

4 The `CARL` Benchmark Library

To analyze how the context and its augmentation influence the agent's generalization capabilities, learning, and behavior, we propose `CARL`: a library for *Context Adaptive Reinforcement Learning* benchmarks following our Contextual Reinforcement Learning formalism. In our release of `CARL` benchmarks, we include and contextually extend classic control and box2d environments from OpenAI Gym (Brockman et al., 2016), Google Brax' walkers (Freeman et al., 2021), a selection from the DeepMind Control Suite (Tassa et al., 2018), an RNA folding environment (Runge et al., 2019) as well as Super Mario levels (Awiszus et al., 2020; Schubert et al., 2021), see Figure 4.

Benchmark Categories Often the physics simulations (brax, box2d, classic control and dm control) define a dynamic body in a static world with similar physical entities like gravity, geometry of the moving body and mass. In our example CARLFetch from Figure 1a the goal is to move the agent to the target area. The

context features joint stiffness, gravity, friction, (joint) angular damping, actuator strength, torso mass as well as target radius and distance define the context and influence the exact instantiation and dynamics of the environment. In principle, the designer is free to select the context features from the set of parameters defining the environment. For Fetch, this could also be limb length of the body. Out of practicality, we choose to vary the most common physical attributes across the environments. When selecting an environment's parameter to become a context feature, it must be guaranteed that the physics and the environment's purpose are not violated, e.g. by setting a negative gravity such that the body flies up and is never able to reach the goal. Please see Appendix G for all registered context features per environment.

Besides physical simulation environments, CARL provides two more specific, challenging environments. The first is the CARLMarioEnv environment built on top of the TOAD-GAN level generator (Awiszus et al., 2020; Schubert et al., 2021). It provides a procedurally generated game-playing environment that allows customization of the generation process. This environment is therefore especially interesting for exploring representation learning for the purpose of learning to better generalize. Secondly, we move closer to real-world application by including the CARLRNADesignEnvironment (Runge et al., 2019). The challenge here is to design RNA sequences given structural constraints. As two different datasets of structures and their instances are used in this benchmark, it is ideally suited for testing policy transfer between RNA structures.

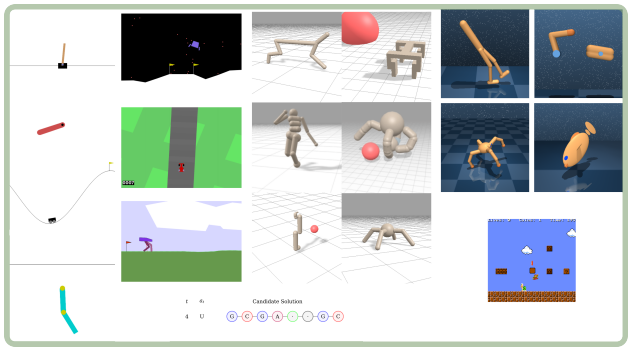


Figure 4: The CARL benchmarks

4.1 Properties of Benchmarks

While the categorization of the CARL benchmarks above provides an overview of the kinds of environments included, we also discuss them in terms of relevant environment attributes that describe the nature of their problem setting, see Figure 5.

State Space Most of our benchmarks have vector-based state spaces, allowing to concatenate context information. Their sizes range from only two state variables in the CARLMountainCar environments to 299 for the CARLHumanoid environment. The notable exceptions here are CARLVehicleRacing and CARLToadGAN, which exclusively use pixel-based observations.

Action Space We provide both discrete and continuous environments, with six requiring discrete actions and the other 14 continuous ones. The number of actions can range from a single action to 19 different actions.

Quality of Reward We cover different types of reward signals with our benchmarks, ranging from relatively sparse step penalty style rewards where the agent only receives a reward of -1 each step to complex composite reward functions in e.g. the Brax-based environments. The latter type is quite informative, providing updates on factors like movement economy and progress toward the goal whereas the former does not let the agents distinguish between transitions without looking at the whole episode. Further examples for sparse rewards are the CARLCartPoleEnv and CARLVehicleRacingEnv.

Context Spaces While the full details of all possible context configurations can be seen in Appendix G, for brevity here we only discuss the differences between context spaces and the configuration possibilities they provide. Depending on the environment the context features have different influences on the dynamics and the reward. Of all 145 registered context features, 99 % influence the dynamics. This means that if a context feature is changed then the transition from states to their successors is affected and likely changed as well. Only 4 % of the context features shape the reward. Most context features (91 %) are continuous; the rest are categorical or discrete.

Summary Comparing our benchmarks along these attributes, we see a wide spread in most of them (Figure 5). CARL focuses on popular environments and will grow over time, increasing the diversity of

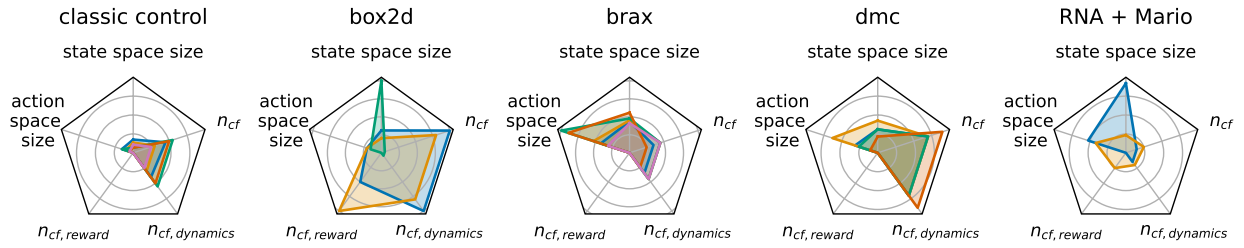


Figure 5: Characteristics of each environment of the environment families showing the action space size, state space size (log-scale), number of context features (n_{cf}), the number of context features directly shaping the reward ($n_{cf,reward}$) and the ones changing the dynamics ($n_{cf,dynamics}$). All axes are scaled to the global extrema and the state space size is additionally on a logarithmic scale.

benchmarks. Already now, `CARL` provides a benchmarking collection that tasks agents with generalizing in addition to solving the problem most common in modern RL while providing a platform for reproducible research.

5 Experiments

Having discussed the framework of cRL and the implications of context in training, we now study several research questions regarding the empirical effects of context: (i) How much does varying context influence performance? Can agents compensate across context variations in a zero-shot manner? (ii) Can we observe the effects discussed in Section 3 in practice? I.e., is there an observable optimality gap on cMDPs, does the context visibility influence the performance and which role does the width of the context distribution play? (iii) How can we assess generalization performance, and how does the test behavior of agents change when exposed to the context information?

To explore our research questions, we use our benchmark library `CARL`. Details about the hyperparameter settings and used hardware for all experiments are listed in Appendix C. In each experiment, if not specified otherwise, we train and evaluate on 10 different random seeds and a set of 128 uniformly sampled contexts. All experiments can be reproduced using the scripts we provide with the benchmark library at `https://anonymous.4open.science/r/CARL-54F4/`.

5.1 How Does Varying Context Influence Performance?

To get an initial understanding on the generalization capabilities, we train a well-known SAC agent (Haarnoja et al., 2018) on the default version of the Pendulum (Brockman et al., 2016) environment. Pendulum is a very simple environment (see Appendix Appendix B for dynamic equations) compared to the majority of RL benchmarks and has been considered solved by deep RL for years. However, we show that we can increase the difficulty of this environment substantially when considering even single context features. The agent is not provided with any explicit information about the context, i.e., it is context-oblivious. Then, for evaluation, we vary each defined context feature by magnitudes $A = 0.1, 0.2, \ldots 2.2$ times the default value for 10 test episodes. In Figure 6, we plot the empirical cumulative distribution functions (eCDF) for the return showing the range of observed returns on the x-axis and the proportion on the y-axis. The further to the right the curve is, the better the observed returns. For the eCDF plots of other `CARL` environments, see Appendix D.2.

First and foremost we observe that some context features do not have an influence on the generalization performance when varied, see Figure 6. Even in this zero-shot setting, the agent performs similarly well on all context variations of the `initial_angle_max` and `initial_velocity_max` features. Yet, the agent's performance is very brittle to other context features, i.e. `max_speed`, simulation timestep `dt`, gravity `g` and length `l`. The trained agent cannot compensate for the effect the context has on the policy and thus performs poorly on several context variations. It is worth noting that the performance curves across the variations depends on the context feature. `max_speed`, for example, is hard for values below $A = 0.7$, but

then the challenge level for the agent decreases abruptly. This transition is smoother for `l` where both very small and very large values are hard to solve. We conclude that it is not straightforward to estimate the impact of changing the environment on agent behavior, especially for physics simulations or similarly complex environments. We also clearly see that zero-shot generalization cannot compensate for variations in environment dynamics. Context variations introduce a significant challenge, even on a simple environment like Pendulum. The next step, therefore, is to train the agent on varying contexts and re-evaluate its generalization performance.

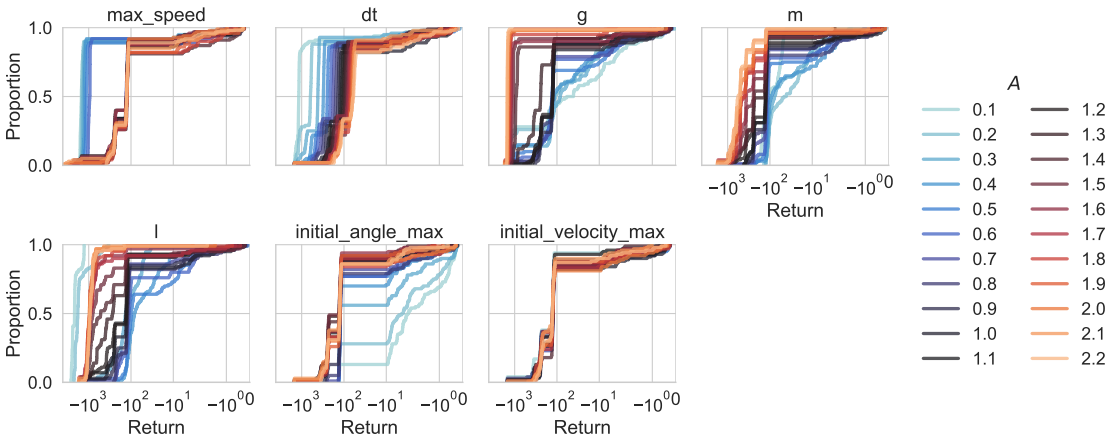


Figure 6: **CARLPendulumEnv**: eCDF Plot. A is the magnitude multiplied with the default value of each context feature. So, $A = 1.0$ refers to the standard environment.

5.2 Does the Optimality Gap Exist in Practice?

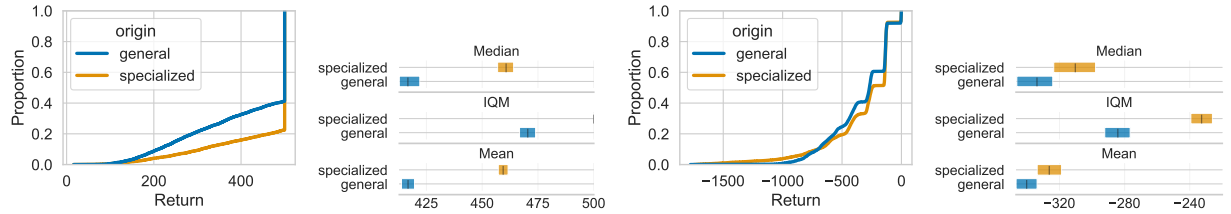
In the previous section, we saw that context variation heavily influences the test performance of a standard agent. Here, we take a closer look and connect this to the Optimality Gap $\mathcal{OG}$ (Equation (1)). In order to demonstrate how significant this gap is in practice, we train a C51 agent (Bellemare et al., 2017) on our contextually extended CartPole environment Brockman et al. (2016) as well as a SAC agent (Haarnoja et al., 2018) on Pendulum. Similarly as above, we use simple environments to demonstrate the induced difficulty by context variation.

To generate instances of both environments, we vary the length of the pole across a uniform distribution $p_{\mathcal{C}} = \mathcal{U}(0.25, 0.75)$ around the standard pole length for CartPole and the pole length across $p_{\mathcal{C}} = \mathcal{U}(1, 2.2)$ for Pendulum. For training, we sample 64 contexts from this distribution and train a general agent which experiences all contexts during training in a round robin fashion. However, we do not explicitly provide the context information to the agent. We approximate the optimal performance by training a separate specialized agent on each context. Afterwards, each agent is evaluated on each context it was trained on for 10 episodes.

Comparing the general and specialized agents, we see a difference of at least 30 reward points in median, mean and estimated IQM performance (as proposed by Agarwal et al. (2021)) for CartPole and a smaller, but similar effect on Pendulum. While this is not a huge decrease in performance, looking at how these rewards are distributed across the evaluation instances shows that the general agent solves significantly fewer instances than the general agent with a decrease of around 40% of finished episodes on CartPole. This shows that while most instances can be solved by the agent one at a time, training an agent that solves all of them jointly is a significant challenge.

5.3 Does Access To Context Improve Training?

We have seen that agents without access to context information are not always able to entirely solve even simple contextual environments. Can these agents improve with access to the context information? We choose a very simple approach of adding either the whole context (concat all) or only the actively changing context feature (concat non-static) to the observation. Obviously this is a simplistic approach that in the case of concat



(a) Return eCDF CartPole (b) Return CartPole (c) Return eCDF Pendulum (d) Return Pendulum

Figure 7: Optimality Gap on CARLCartPole (left) and CARLPendulum (right).

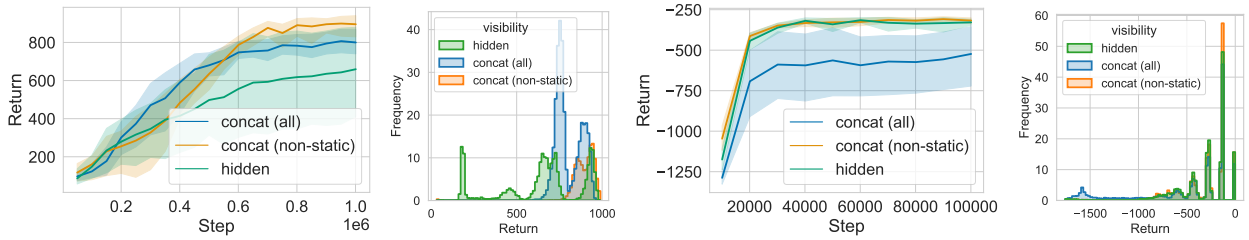


Figure 8: Train (left) and test performance (right) of agents with visible and hidden context on CARLDmcWalker with different viscosity values and 5 seeds (top) and CARLPendulum with different lengths and 20 seeds (bottom). Shown is the mean performance with 95% confidence interval and testing across 200 test contexts.

all significantly alters the size of the observation. Though, even with this simple idea, training performance improves by a large margin in some cases, see Figure 8. Here, the agent, this time on CARLDmcWalker with changing viscosity ($\sim \mathcal{U}[1, 2.5]$ times the default value), learns faster, is more stable, and reaches a higher final performance with the additional information added to the observation. In testing, we see significantly more failures in the hidden agent compared to the concat ones, with only the concat non-static agent learning to solve the contextual environment without a large decrease in overall test performance. Effective generalization seems to be a matter of a reasonable feature set, similar to supervised learning.

On Pendulum, however, this is not the case; we see no meaningful difference in mean performance of concat (non-static) and hidden when varying length ($\sim \mathcal{U}[1, 2.2]$ times the default value). Please note that the large confidence interval stems from runs where the algorithm did not find a meaningful performance, see Appendix Figure 19. The concat agents perform better on some unseen contexts in evaluation, though the hidden agent is far superior on a slice of the instance set. We expect the reason for these mixed results to be that simply appending the context to the observation is not an ideal way to communicate these complex environmental factors. Instead, context embeddings could be a more potent way of capturing the way a context feature changes an environment, as we have seen in some prior work on incorporating goals (Sukhbaatar et al., 2018; Liu et al., 2022) into training. Since our goal was to show the potential of context information, we leave it to future work to investigate better representations of context features.

5.4 How Far Can Agents Learn To Act Across Contexts?

As we saw different evaluation behaviors from hidden and visible agents in the last section, we want to further investigate their generalization capabilities in- and out-of-distribution. To this end, we follow a three mode evaluation protocol for Contextual Reinforcement Learning that tests the agent's interpolation capabilities and out-of-distribution generalization under different training distribution shapes (Kirk et al., 2023). This is in contrast to PCG environments where we cannot define evaluation protocols and instead have to rely on the given instance generation procedure.

We define train and test distributions for each dimension of the context space individually, allowing us to study different relationships between train and test settings. If at least parts of the test context are within the train distribution, we speak of interpolation, if the whole context is outside, of extrapolation. By choosing

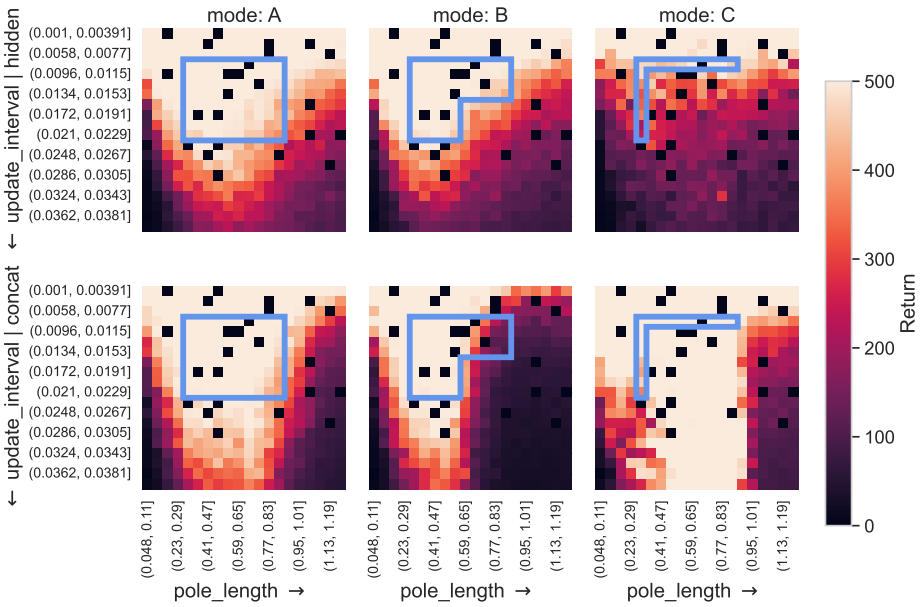


Figure 9: In- and Out-of-Distribution Generalization on CartPole. We vary the pole length and update_interval. The blue polygon marks the train context area. Black dots mark gaps in the context space due to random sampling. First row: Context-oblivious agent, second row: Concat.

two context features and defining uniform train distributions on both, we construct a convex training set in the context feature space (mode A: □). The context feature distributions can also be defined to allow only a small variation (mode B: ⊾) or a single value per feature (mode C: ∟), creating non-convex train sets. Thus, the convex hull of this non-convex set tests combinatorial interpolation.

To demonstrate this, we again choose contextual CartPole (Brockman et al., 2016) from `CARL`, and the C51 (Bellemare et al., 2017) agent known to perform well on it. We train the agent for 100 000 timesteps and vary the update_interval and the pole length in the environment, once without access to the context (hidden) and once concatenating pole length and gravity to the observation (concat). We repeat this with 10 random seeds and 5 test episodes per context. For the train and test context sets, we sample 1000 contexts each for the train and test distributions defined in the evaluation protocol, see Figure 9. The test performances are discretized and aggregated across seeds with the interquartile mean (25th-75th quartile).

In Figure 9, we show that both hidden (context-oblivious) and visible (concatenate) agents perform fairly well within their training distribution for evaluation mode A and even generalize to fairly large areas of the test distribution, more so for concat. Large update intervals combined with extreme pole lengths proves to be the most challenging area.

Interestingly, the concat agent is able to solve more of the large update intervals in contrast to the hidden agent which is most pronounced on train distribution C. This itself is counterintuitive, we would expect that the larger the train distribution, the larger the out-of-distribution generalization. The hidden agent in general performs well for low update intervals. This resonates with the intuition that smaller update intervals are easier because there is more granularity (and time) to react to the current state. In addition, we provide results for varying the update interval and the gravity. Here, the results are similar but subdued, see Appendix Figure 20. Varying the pole length together with the gravity paints a different image (Appendix Figure 21. In this case, the hidden agent performs much better. We suspect that the effects of gravity and pole length cancel out and thus context information is not needed to learn a meaningful policy. These three variations again show that providing context by concatenation *can* be helpful but not in every case, demanding further investigation on alternatives. Finally, neither agent shows reliable combinatorial interpolation performance, let alone out-of-distribution generalization. We see here a major open challenge for the RL community, for which `CARL` will support them in the development and precise studies of RL generalization capabilities.

6 Related Work

Transferring and generalizing the performance of an RL agent from its training setting to some test variation has been at the center of several sub-communities within RL. Robustness, for example, can be seen as a subcategory of generalization where variations to the context are usually kept small, and the goal is to avoid failures due to exceptions on a single task (Morimoto & Doya, 2000; Pinto et al., 2017; Mehta et al., 2019; Zhang et al., 2021d). Policy transfer is also concerned with generalization in a sense, though here the goal has often been fine-tuning a pre-trained policy, i.e., few-shot generalization instead of zero-shot generalization (Duan et al., 2016; Finn et al., 2017; Nichol et al., 2018). The goal in Multi-Task Learning is to learn a fixed set of tasks efficiently (Yu et al., 2019), not necessarily being concerned with generalizing outside of this set. Meta-Learning in RL usually aims at zero-shot policy generalization similar to Contextual Reinforcement Learning (cRL). This field is very broad with different approaches like learning to learn algorithms or their components (Schulman et al., 2016; Duan et al., 2016; Wang et al., 2017), generating task curricula (Matiisen et al., 2020; Nguyen et al., 2021) or meta-learning hyperparameters (Runge et al., 2019; Zhang et al., 2021c).

The previously mentioned methods were not conceived with cRL in mind but use context implicitly. Many meta-RL methods, however, can or do make use of context information to guide their optimization, either directly (Klink et al., 2020; Eimer et al., 2021) or by utilizing a learnt dynamics model (Kober et al., 2012). The idea of context-aware dynamics models has also been applied to model-based RL (Lee et al., 2020b). These approaches use context in different ways to accomplish some generalization goal, e.g. zero-shot generalization to a test distribution or solving a single hard instance. In contrast, we do not propose a specific Meta-Learning method but examine the foundations of cRL and how context affects policy learning in general.

Zero-shot generalization across a distribution of contexts, specifically, has become a common goal in standard RL environments, often in the form of generalization across more or less randomly generated tasks (Juliani et al., 2019; Cobbe et al., 2020; Samvelyan et al., 2021). The larger the degree of randomness in the generation procedure, however, the less context information and control are available for Meta-Learning methods (Kirk et al., 2023). Such underspecification of tasks can even make evaluations more challenging (Jayawardana et al., 2022). In contrast to other works on generalization in RL, we therefore focus on sampling context without PCG but from explicitly defined distributions. This allows us to analyze the capabilities of our agents in a more fine-grained manner, e.g. how far away from their training distribution generalization performance starts to decrease, instead of relying only on the test reward across all task instances. Whiteson et al. (2011) propose an evaluation protocol for general RL to avoid overfitting on particular training environments, where they argue for generalized methodologies assessing the performance of an agent on a set or distribution of environments. cMDPs easily fit into this line of evaluation protocols with the advantage of interpretable generalization capabilities because of the definition of interpretable context features. Kirk et al. (2021) similarly propose evaluation protocols, but already with cMDPs in mind. For further ways cRL opens new directions in ongoing work, see Appendix F.

7 Conclusion

Toward our goal of creating general and robust agents, we need to factor in possible changes in the environment. We model these changes with the framework of contextual Reinforcement Learning (cRL) and reason about what demands Contextual Reinforcement Learning introduces to the agents and the learning process, specifically regarding the suboptimal nature of conventional RL policies in cRL. With `CARL`, we provide a benchmark library which contextualizes popular benchmarks and is designed to study generalization in Contextual Reinforcement Learning. It allows us to empirically demonstrate that contextual changes disturb learning even in simple settings and that the final performance and the difficulty correlate with the magnitude of the variation. We also verify that context-oblivious policies are not able to fully solve even simple contextual environments, as indicated by our theoretical discussion. We expect this to be a first step towards better solution mechanisms for contextual RL problems and therefore one step closer to general and robust agents.

Broader Impact Statement

We foresee no new direct societal and ethical implications other than the known concerns regarding autonomous agents and RL (e.g., in a military context).

References

M. Abdolshah, H. Le, T. K. George, S. Gupta, S. Rana, and S. Venkatesh. A new representation of successor features for transfer across dissimilar environments. In M. Meila and T. Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 1–9. PMLR, 18–24 Jul 2021.

S. Adriaensen, A. Biedenkapp, G. Shala, N. Awad, T. Eimer, M. Lindauer, and F. Hutter. Automated dynamic algorithm configuration. *J. Artif. Intell. Res.*, 75:1633–1699, 2022.

R. Agarwal, M. Schwarzer, P. Castro, A. Courville, and M. Bellemare. Deep reinforcement learning at the edge of the statistical precipice. In *Proceedings of the 35th International Conference on Advances in Neural Information Processing Systems (NeurIPS'21)*, pp. 29304–29320, 2021.

L. Alegre, A. Bazzan, and B. da Silva. Minimum-delay adaptation in non-stationary reinforcement learning via online high-confidence change-point detection. In *AAMAS '21: 20th International Conference on Autonomous Agents and Multiagent Systems*, pp. 97–105. ACM, 2021.

I. Arel, C. Liu, T. Urbanik, and A. Kohls. Reinforcement learning-based multi-agent system for network traffic signal control. *IET Intelligent Transport Systems*, 4(2):128–135, 2010.

M. Awiszus, F. Schubert, and B. Rosenhahn. TOAD-GAN: Coherent style level generation from a single example. In *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, volume 16, October 2020.

A. Badia, B. Piot, S. Kapturowski, P. Sprechmann, A. Vitvitskyi, Z. Guo, and C. Blundell. Agent57: Outperforming the atari human benchmark. In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, volume 119 of *Proceedings of Machine Learning Research*, pp. 507–517. PMLR, 2020.

M. G. Bellemare, S. Srinivasan, G. Ostrovski, T. Schaul, D. Saxton, and R. Munos. Unifying count-based exploration and intrinsic motivation. In D. Lee, M. Sugiyama, U. von Luxburg, I. Guyon, and R. Garnett (eds.), *Proceedings of the 29th International Conference on Advances in Neural Information Processing Systems (NeurIPS'16)*, pp. 1471–1479, 2016.

Marc G. Bellemare, Will Dabney, and Rémi Munos. A distributional perspective on reinforcement learning. In Doina Precup and Yee Whye Teh (eds.), *Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017*, volume 70 of *Proceedings of Machine Learning Research*, pp. 449–458. PMLR, 2017. URL `http://proceedings.mlr.press/v70/bellemare17a.html`.

A. Biedenkapp, J. Marben, M. Lindauer, and F. Hutter. CAVE: Configuration assessment, visualization and evaluation. In *Proceedings of the International Conference on Learning and Intelligent Optimization (LION)*, Lecture Notes in Computer Science. Springer, 2018.

A. Biedenkapp, H. F. Bozkurt, T. Eimer, F. Hutter, and M. Lindauer. Dynamic Algorithm Configuration: Foundation of a New Meta-Algorithmic Framework. In J. Lang, G. De Giacomo, B. Dilkina, and M. Milano (eds.), *Proceedings of the Twenty-fourth European Conference on Artificial Intelligence (ECAI'20)*, pp. 427–434, June 2020.

Craig Boutilier, Thomas L. Dean, and Steve Hanks. Decision-theoretic planning: Structural assumptions and computational leverage. *J. Artif. Intell. Res.*, 11:1–94, 1999. doi: 10.1613/jair.575. URL `https://doi.org/10.1613/jair.575`.

G. Brockman, V. Cheung, L. Pettersson, J. Schneider, J. Schulman, J. Tang, and W. Zaremba. Openai gym. *CoRR*, abs/1606.01540, 2016.

P. Castro, T. Kastner, P. Panangaden, and M. Rowland. Mico: Learning improved representations via sampling-based state similarity for markov decision processes. *CoRR*, abs/2106.08229, 2021.

K. Cobbe, C. Hesse, J. Hilton, and J. Schulman. Leveraging procedural generation to benchmark reinforcement learning. In *Proceedings of the 37th International Conference on Machine Learning, ICML*, volume 119 of *Proceedings of Machine Learning Research*, pp. 2048–2056. PMLR, 2020.

B. da Silva, E. Basso, A. Bazzan, and P. Engel. Dealing with non-stationary environments using context detection. In *Machine Learning, Proceedings of the Twenty-Third International Conference (ICML*, volume 148 of *ACM International Conference Proceeding Series*, pp. 217–224. ACM, 2006.

B. da Silva, G. Konidaris, and A. Barto. Learning parameterized skills. In *Proceedings of the 29th International Conference on Machine Learning, ICML*, 2012.

J. Degrave, F. Felici, J. Buchli, M. Neunert, B. Tracey, F. Carpanese, T. Ewalds, R. Hafner, A. Abdolmaleki, D. de Las Casas, C. Donner, L. Fritz, C. Galperti, A. Huber, J. Keeling, M. Tsimpoukelli, J. Kay, A. Merle, J. Moret, S. Noury, F. Pesamosca, D. Pfau, O. Sauter, C. Sommariva, S. Coda, B. Duval, A. Fasoli, P. Kohli, K. Kavukcuoglu, D. Hassabis, and M. Riedmiller. Magnetic control of tokamak plasmas through deep reinforcement learning. *Nature*, 602(7897):414–419, 2022.

F. Doshi-Velez and G. Dimitri Konidaris. Hidden parameter markov decision processes: A semiparametric regression approach for discovering latent task parametrizations. In *Proceedings of the Twenty-Fifth International Joint Conference on Artificial Intelligence, IJCAI*, pp. 1432–1440. IJCAI/AAAI Press, 2016.

S. Du, A. Krishnamurthy, N. Jiang, A. Agarwal, M. Dudík, and J. Langford. Provably efficient RL with rich observations via latent state decoding. In *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, volume 97 of *Proceedings of Machine Learning Research*, pp. 1665–1674. PMLR, 2019.

Y. Duan, J. Schulman, X. Chen, P. Bartlett, I. Sutskever, and P. Abbeel. Rl$ˆ2$: Fast reinforcement learning via slow reinforcement learning. *CoRR*, abs/1611.02779, 2016.

T. Eimer, A. Biedenkapp, F. Hutter, and M. Lindauer. Self-paced context evaluation for contextual reinforcement learning. In M. Meila and T. Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning (ICML'21)*, volume 139 of *Proceedings of Machine Learning Research*, pp. 2948–2958. PMLR, 2021.

B. Eysenbach, R. Salakhutdinov, and S. Levine. Search on the replay buffer: Bridging planning and reinforcement learning. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett (eds.), *Proceedings of the 32nd International Conference on Advances in Neural Information Processing Systems (NeurIPS'19)*, pp. 15220–15231, 2019.

C. Finn, P. Abbeel, and S. Levine. Model-agnostic meta-learning for fast adaptation of deep networks. In D. Precup and Y. Teh (eds.), *Proceedings of the 34th International Conference on Machine Learning (ICML'17)*, volume 70, pp. 1126–1135. Proceedings of Machine Learning Research, 2017.

C. Florensa, D. Held, X. Geng, and P. Abbeel. Automatic goal generation for reinforcement learning agents. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018*, volume 80 of *Proceedings of Machine Learning Research*, pp. 1514–1523. PMLR, 2018.

J. Franke, G. Köhler, A. Biedenkapp, and F. Hutter. Sample-efficient automated deep reinforcement learning. In *9th International Conference on Learning Representations, ICLR*. OpenReview.net, 2021.

C. Freeman, E. Frey, A. Raichuk, S. Girgin, I. Mordatch, and O. Bachem. Brax - A differentiable physics engine for large scale rigid body simulation. *CoRR*, abs/2106.13281, 2021.

H. Fu, H. Tang, J. Hao, C. Chen, X. Feng, D. Li, and W. Liu. Towards effective context for meta-reinforcement learning: an approach based on contrastive learning. In *Proceedings of the Conference on Artificial Intelligence (AAAI'21)*, pp. 7457–7465. AAAI Press, 2021a.

X. Fu, G. Yang, P. Agrawal, and T. Jaakkola. Learning task informed abstractions. In M. Meila and T. Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 3480–3491. PMLR, 18–24 Jul 2021b.

C. Gelada, S. Kumar, J. Buckman, O. Nachum, and M. Bellemare. Deepmdp: Learning continuous latent space models for representation learning. In *Proceedings of the 36th International Conference on Machine Learning, ICML*, volume 97 of *Proceedings of Machine Learning Research*, pp. 2170–2179. PMLR, 2019.

Dibya Ghosh, Jad Rahme, Aviral Kumar, Amy Zhang, Ryan P. Adams, and Sergey Levine. Why generalization in RL is difficult: Epistemic pomdps and implicit partial observability. *CoRR*, abs/2107.06277, 2021. URL `https://arxiv.org/abs/2107.06277`.

C. Guestrin, D. Koller, and R. Parr. Multiagent planning with factored mdps. In *Advances in Neural Information Processing Systems 14 [Neural Information Processing Systems: Natural and Synthetic, NIPS*, pp. 1523–1530. MIT Press, 2001.

T. Haarnoja, A. Zhou, P. Abbeel, and S. Levine. Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor. In *Proceedings of the 35th International Conference on Machine Learning, ICML*, volume 80 of *Proceedings of Machine Learning Research*, pp. 1856–1865. PMLR, 2018.

A. Hallak, D. Di Castro, and S. Mannor. Contextual markov decision processes. *arXiv:1502.02259 [stat.ML]*, 2015.

P. Henderson, R. Islam, P. Bachman, J. Pineau, D. Precup, and D. Meger. Deep reinforcement learning that matters. In S. McIlraith and K. Weinberger (eds.), *Proceedings of the Conference on Artificial Intelligence (AAAI'18)*. AAAI Press, 2018.

K. Holsheimer, F. Schubert, B. Beilharz, and L. Tsao. Coax: Plug-n-play reinforcement learning in python with gymnasium and jax. `https://github.com/coax-dev/coax`, 2023.

V. J. Parker-Holder, S. J. Nguyen, and Roberts. Provably efficient online hyperparameter optimization with population-based bandits. In H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (eds.), *Proceedings of the 33rd International Conference on Advances in Neural Information Processing Systems (NeurIPS'20)*, volume 33, pp. 17200–17211, 2020.

M. Jaderberg, V. Dalibard, S. Osindero, W. Czarnecki, J. Donahue, A. Razavi, O. Vinyals, T. Green, I. Dunning, K. Simonyan, C. Fernando, and K. Kavukcuoglu. Population based training of neural networks. *arXiv:1711.09846 [cs.LG]*, 2017a.

M. Jaderberg, V. Mnih, W. Czarnecki, T. Schaul, J. Leibo, D. Silver, and K. Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. In *5th International Conference on Learning Representations, ICLR*. OpenReview.net, 2017b.

V. Jayawardana, C. Tang, S. Li, D. Suo, and C. Wu. The impact of task underspecification in evaluating deep reinforcement learning. *CoRR*, abs/2210.08607, 2022.

A. Juliani, A. Khalifa, V. Berges, J. Harper, E. Teng, H. Henry, A. Crespi, J. Togelius, and D. Lange. Obstacle tower: A generalization challenge in vision, control, and planning. In *Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, IJCAI*, pp. 2684–2691. ijcai.org, 2019.

R. Kirk, A. Zhang, E. Grefenstette, and T. Rocktäschel. A survey of generalisation in deep reinforcement learning. *CoRR*, abs/2111.09794, 2021.

R. Kirk, A. Zhang, E. Grefenstette, and T. Rocktäschel. A survey of zero-shot generalisation in deep reinforcement learning. *J. Artif. Intell. Res.*, 76:201–264, 2023.

P. Klink, C. D'Eramo, J. Peters, and J. Pajarinen. Self-paced deep reinforcement learning. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS*, 2020.

J. Kober, A. Wilhelm, E. Öztop, and J. Peters. Reinforcement learning to adjust parametrized motor primitives to new situations. *Autonomous Robots*, 33(4):361–379, 2012.

R. Koppejan and S. Whiteson. Neuroevolutionary reinforcement learning for generalized helicopter control. In *Proceedings of the 11th Annual conference on Genetic and evolutionary computation*, GECCO '09, pp. 145–152. Association for Computing Machinery, 2009.

J. Kostas, Y. Chandak, S. Jordan, G. Theocharous, and P. Thomas. High confidence generalization for reinforcement learning. In Marina Meila and Tong Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 5764–5773. PMLR, 18–24 Jul 2021.

H. Küttler, N. Nardelli, A. Miller, R. Raileanu, M. Selvatici, E. Grefenstette, and T. Rocktäschel. The nethack learning environment. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020*, 2020.

J. Lee, J. Hwangbo, L. Wellhausen, V. Koltun, and M. Hutter. Learning quadrupedal locomotion over challenging terrain. *Science in Robotics*, 5, 2020a.

K. Lee, Y. Seo, S. Lee, H. Lee, and J. Shin. Context-aware dynamics model for generalization in model-based reinforcement learning. In *Proceedings of the 37th International Conference on Machine Learning, ICML*, volume 119 of *Proceedings of Machine Learning Research*, pp. 5757–5766. PMLR, 2020b.

X. Li, J. Zhang, J. Bian, Y. Tong, and T. Liu. A cooperative multi-agent reinforcement learning framework for resource balancing in complex logistics network. In *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems, AAMAS*, pp. 980–988. International Foundation for Autonomous Agents and Multiagent Systems, 2019.

M. Liu, M. Zhu, and W. Zhang. Goal-conditioned reinforcement learning: Problems and solutions. In Luc De Raedt (ed.), *Proceedings of the Thirty-First International Joint Conference on Artificial Intelligence, IJCAI*, pp. 5502–5511. ijcai.org, 2022.

M. Lu, Z. Shahn, D. Sow, F. Doshi-Velez, and L. H. Lehman. Is deep reinforcement learning ready for practical applications in healthcare? A sensitivity analysis of duel-ddqn for hemodynamic management in sepsis patients. In *AMIA 2020, American Medical Informatics Association Annual Symposium, Virtual Event, USA, November 14-18, 2020*. AMIA, 2020.

M. Machado, M. Bellemare, E. Talvitie, J. Veness, M. Hausknecht, and M. Bowling. Revisiting the arcade learning environment: Evaluation protocols and open problems for general agents. *J. Artif. Intell. Res.*, 61: 523–562, 2018.

D. Malik, Y. Li, and P. Ravikumar. When is generalizable reinforcement learning tractable? In Marc'Aurelio Ranzato, Alina Beygelzimer, Yann N. Dauphin, Percy Liang, and Jennifer Wortman Vaughan (eds.), *Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS*, pp. 8032–8045, 2021.

T. Matiisen, A. Oliver, T. Cohen, and J. Schulman. Teacher-student curriculum learning. *IEEE Trans. Neural Networks Learn. Syst.*, 31(9):3732–3740, 2020.

B. Mehta, M. Diaz, F. Golemo, C. Pal, and L. Paull. Active domain randomization. In Leslie Pack Kaelbling, Danica Kragic, and Komei Sugiura (eds.), *3rd Annual Conference on Robot Learning, CoRL*, volume 100 of *Proceedings of Machine Learning Research*, pp. 1162–1176. PMLR, 2019.

T. Meng and M. Khushi. Reinforcement learning in financial markets. *Data*, 4(3):110, 2019.

A. Modi, N. Jiang, S. P. Singh, and A. Tewari. Markov decision processes with continuous side information. In *Algorithmic Learning Theory (ALT'18)*, volume 83, pp. 597–618, 2018.

J. Morimoto and K. Doya. Robust reinforcement learning. In Todd K. Leen, Thomas G. Dietterich, and Volker Tresp (eds.), *Advances in Neural Information Processing Systems 13, Papers from Neural Information Processing Systems (NIPS) 2000, Denver, CO, USA*, pp. 1061–1067. MIT Press, 2000.

S. Nguyen, N. Duminy, A. Manoury, D.e Duhaut, and C. Buche. Robots learn increasingly complex tasks with intrinsic motivation and automatic curriculum learning. *Künstliche Intell.*, 35(1):81–90, 2021.

A. Nichol, J. Achiam, and J. Schulman. On first-order meta-learning algorithms. *CoRR*, abs/1803.02999, 2018. URL `http://arxiv.org/abs/1803.02999`.

J. Parker-Holder, R. Rajan, X. Song, A. Biedenkapp, Y. Miao, T. Eimer, B. Zhang, V. Nguyen, R. Calandra, A. Faust, F. Hutter, and M. Lindauer. Automated reinforcement learning (autorl): A survey and open problems. *J. Artif. Intell. Res.*, 74:517–568, 2022.

L. Pinto, J. Davidson, R. Sukthankar, and A. Gupta. Robust adversarial reinforcement learning. In Doina Precup and Yee Whye Teh (eds.), *Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017*, volume 70 of *Proceedings of Machine Learning Research*, pp. 2817–2826. PMLR, 2017.

Kai Ploeger, Michael Lutter, and Jan Peters. High acceleration reinforcement learning for real-world juggling with binary rewards. In Jens Kober, Fabio Ramos, and Claire J. Tomlin (eds.), *4th Conference on Robot Learning, CoRL 2020, 16-18 November 2020, Virtual Event / Cambridge, MA, USA*, volume 155 of *Proceedings of Machine Learning Research*, pp. 642–653. PMLR, 2020. URL `https://proceedings.mlr.press/v155/ploeger21a.html`.

M. Ponsen, M. Taylor, and K. Tuyls. Abstraction and generalization in reinforcement learning: A summary and framework. In *Adaptive and Learning Agents, Second Workshop, ALA 2009, Held as Part of the AAMAS 2009 Conference in Budapest*, volume 5924 of *Lecture Notes in Computer Science*, pp. 1–32. Springer, 2009.

K. Rakelly, A. Zhou, C. Finn, S. Levine, and D. Quillen. Efficient off-policy meta-reinforcement learning via probabilistic context variables. In K. Chaudhuri and R. Salakhutdinov (eds.), *Proceedings of the 36th International Conference on Machine Learning (ICML'19)*, volume 97, pp. 5331–5340. PMLR, 2019.

J. Rice. The algorithm selection problem. *Advances in Computers*, 15:65–118, 1976.

F. Runge, D. Stoll, S. Falkner, and F. Hutter. Learning to Design RNA. In *Proceedings of the International Conference on Learning Representations (ICLR'19)*, 2019. Published online: `iclr.cc`.

M. Samvelyan, R. Kirk, V. Kurin, J. Parker-Holder, M. Jiang, E. Hambro, F. Petroni, H. Küttler, E. Grefenstette, and T. Rocktäschel. Minihack the planet: A sandbox for open-ended reinforcement learning research. In Joaquin Vanschoren and Sai-Kit Yeung (eds.), *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks*, 2021.

T. Schaul, D. Horgan, K. Gregor, and D. Silver. Universal value function approximators. In F. R. Bach and D. M. Blei (eds.), *Proceedings of the 32nd International Conference on Machine Learning (ICML'15)*, volume 37, pp. 1312–1320. Omnipress, 2015.

F. Schubert, M. Awiszus, and B. Rosenhahn. Toad-gan: a flexible framework for few-shot level generation in token-based games. *IEEE Transactions on Games*, pp. 1–1, 2021. doi: 10.1109/TG.2021.3069833.

J. Schulman, P. Moritz, S. Levine, M. Jordan, and P. Abbeel. High-dimensional continuous control using generalized advantage estimation. In Yoshua Bengio and Yann LeCun (eds.), *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016.

D. Silver, A. Huang, C. Maddison, A. Guez, L. Sifre, G. Driessche, J. Schrittwieser, I. Antonoglou, V. Panneershelvam, M. Lanctot, S. Dieleman, D. Grewe, J. Nham, N. Kalchbrenner, I. Sutskever, T. Lillicrap, M. Leach, K. Kavukcuoglu, T. Graepel, and D. Hassabis. Mastering the game of go with deep neural networks and tree search. *Nature*, 529(7587):484–489, 2016.

S. Sodhani, L. Denoyer, P. Kamienny, and O. Delalleau. Mtenv - environment interface for mulit-task reinforcement learning. Github, 2021a. URL `https://github.com/facebookresearch/mtenv`.

S. Sodhani, A. Zhang, and J. Pineau. Multi-task reinforcement learning with context-based representations. In M. Meila and T. Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 9767–9779. PMLR, 18–24 Jul 2021b.

S. Sukhbaatar, E. Denton, A. Szlam, and R. Fergus. Learning goal embeddings via self-play for hierarchical reinforcement learning. *CoRR*, abs/1811.09083, 2018.

Y. Tassa, Y. Doron, A. Muldal, T. Erez, Y. Li, D. de Las Casas, D. Budden, A. Abdolmaleki, J. Merel, A. Lefrancq, T. Lillicrap, and M. Riedmiller. Deepmind control suite. *CoRR*, abs/1801.00690, 2018. URL `http://arxiv.org/abs/1801.00690`.

J. van Rijn and F. Hutter. Hyperparameter importance across datasets. In Y. Guo and F.Farooq (eds.), *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD)*, pp. 2367–2376. ACM Press, 2018.

J. Wang, Z. Kurth-Nelson, H. Soyer, J. Leibo, D. Tirumala, R. Munos, C. Blundell, D. Kumaran, and M. Botvinick. Learning to reinforcement learn. In G. Gunzelmann, A. Howes, T. Tenbrink, and E. Davelaar (eds.), *Proceedings of the 39th Annual Meeting of the Cognitive Science Society*. cognitivesciencesociety.org, 2017.

J. Wang, M. King, N. Porcel, Z. Kurth-Nelson, T. Zhu, C. Deck, P. Choy, M. Cassin, M. Reynolds, H. Song, G. Buttimore, D. Reichert, N. Rabinowitz, L. Matthey, D. Hassabis, A. Lerchner, and M. Botvinick. Alchemy: A benchmark and analysis toolkit for meta-reinforcement learning agents. In Joaquin Vanschoren and Sai-Kit Yeung (eds.), *Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks*, 2021.

S. Whiteson, B. Tanner, M. Taylor, and P. Stone. Protecting against evaluation overfitting in empirical reinforcement learning. In *2011 IEEE Symposium on Adaptive Dynamic Programming and Reinforcement Learning (ADPRL)*, pp. 120–127, 2011.

L. Xu, H. Hoos, and K. Leyton-Brown. Hydra: Automatically configuring algorithms for portfolio-based selection. In M. Fox and D. Poole (eds.), *Proceedings of the Twenty-fourth National Conference on Artificial Intelligence (AAAI'10)*, pp. 210–216. AAAI Press, 2010.

D. Yarats, R. Fergus, A. Lazaric, and L. Pinto. Reinforcement learning with prototypical representations. In M. Meila and T. Zhang (eds.), *Proceedings of the 38th International Conference on Machine Learning*, volume 139 of *Proceedings of Machine Learning Research*, pp. 11920–11931. PMLR, 18–24 Jul 2021.

T. Yu, D. Quillen, Z. He, R. Julian, K. Hausman, C. Finn, and S. Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. In *Conference on Robot Learning (CoRL)*, 2019.

A. Zhang, R. Thomas McAllister, R. Calandra, Y. Gal, and S. Levine. Learning invariant representations for reinforcement learning without reconstruction. In *9th International Conference on Learning Representations, ICLR*. OpenReview.net, 2021a.

A. Zhang, S. Sodhani, K. Khetarpal, and J. Pineau. Learning robust state abstractions for hidden-parameter block mdps. In *9th International Conference on Learning Representations, ICLR 2021*. OpenReview.net, 2021b.

B. Zhang, R. Rajan, L. Pineda, N. Lambert, A. Biedenkapp, K. Chua, F. Hutter, and R. Calandra. On the importance of hyperparameter optimization for model-based reinforcement learning. In *The 24th International Conference on Artificial Intelligence and Statistics, AISTATS*, volume 130 of *Proceedings of Machine Learning Research*, pp. 4015–4023. PMLR, 2021c.

H. Zhang, H. Chen, D. Boning, and C. Hsieh. Robust reinforcement learning on state observations with learned optimal adversary. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net, 2021d.

W. Zhou, L. Pinto, and A. Gupta. Environment probing interaction policies. In *Proceedings of the International Conference on Learning Representations (ICLR'19)*, 2019. Published online: `iclr.cc`.

Z. Zhou, X. Li, and R. Zare. Optimizing chemical reactions with deep reinforcement learning. *ACS central science*, 3(12):1337–1344, 2017.

Z. Zhu, K. Lin, and J. Zhou. Transfer learning in deep reinforcement learning: A survey. *CoRR*, abs/2009.07888, 2020.

Appendix

A Partial Observability in cMDPs

Discussing the visibility of context for an agent can be linked to the partial observability we see in POMDPs. We believe it is useful to differentiate between the visibility of context and state features or observations as both serve a different function in a cMDP. The state features describe the current state while the context describes the current MDP. Therefore making one only partially observable should influence the learning dynamics in different ways. Therefore we define a cMDP as a special case of a POMDP, analogous to Kirk et al. (2023), where we have an emission function $\phi : \mathcal{S} \times p_{\mathcal{C}} \to O_s \times O_c$ mapping the state space to some state observation space O_s and context observation space O_c. ϕ differentiates between state s and context c to allow different degrees of observability in state and context, e.g. hiding the context completely but exposing the whole state, in order to enable more flexible learning. It can also introduce the additional challenge of learning from imperfect or noisy context information.

B Pendulum's Dynamic Equations

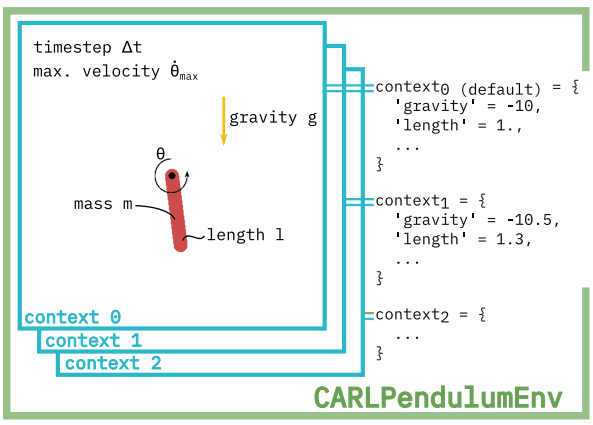


Figure 10: CARLPendulumEnv

Because we use CARLPendulumEnv embedding gym's Pendulum (Brockman et al., 2016) for our task variation experiment (see Section 5.1), we provide the dynamic equations to show the simplicity of the system. The state and observation consists of the angular position θ and velocity $\dot{\theta}$ of the pendulum. The discrete equation defining the behavior of the environment is defined as follows:

$$\dot{\theta}_{k+1} = \dot{\theta}_k + \left(-\frac{3g}{2l} \sin(\theta_k + \pi) + \frac{3}{m \cdot l^2} u_k \right) \cdot \Delta t$$
$$\theta_{k+1} = \theta_k + \dot{\theta}_{k+1} \cdot \Delta t \,.$$

Here, k is the index of the iteration/step. The dynamic system is parametrized by the context, which consists of g the gravity, l and m the length and mass of the pendulum, u the control input and Δt the timestep. Figure 10 shows how Pendulum is embedded in `CARL`.

C Hyperparameters and Hardware

Hyperparameters and Training Details We implemented our own agents using coax (Holsheimer et al., 2023) with hyperparameters specified in Table 1. All experiments can be reproduced using the scripts we provide with the benchmark library at `https://anonymous.4open.science/r/CARL-54F4/`.

Hardware All experiments on all benchmarks were conducted on a slurm CPU and GPU cluster (see Table 2). On the CPU partition there are 1592 CPUs available across nodes.

D Additional Experimental Results

In this section, we provide additional information and results for our experiments section (section 5).

Table 1: Hyperparameters for algorithm and environment combinations

algorithm	c51	c51	sac	c51	c51	sac	sac	sac
env	CartPole	Acrobot	Pendulum	MountainCar	LunarLander	DmcWalker	DmcQuadruped	Halfcheetah
n_step	5	5	5	5	5	5	5	5
gamma	0.99	0.99	0.9	0.99	0.99	0.9	0.9	0.99
alpha	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.1
batch_size	128	128	128	128	128	128	128	256
learning_rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.0001
q_targ_tau	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.005
warmup_num_frames	5000	5000	5000	5000	5000	5000	5000	5000
pi_warmup_num_frames	7500	7500	7500	7500	7500	7500	7500	7500
pi_update_freq	4	4	4	4	4	4	4	2
replay_capacity	100000	100000	100000	100000	100000	100000	100000	1000000
network	{'width': 256, 'num_atoms': 51}	{'width': 256, 'num_atoms': 51}	{'width': 256}	{'width': 32, 'num_atoms': 51}	{'width': 256, 'num_atoms': 51}	{'width': 256}	{'width': 256}	{'width': 1024}
pi_temperature	0.1	0.1	NaN	0.1	0.1	NaN	NaN	NaN
q_min_value	0.0	-50.0	NaN	-100.0	-100.0	NaN	NaN	NaN
q_max_value	110.0	0.0	NaN	100.0	100.0	NaN	NaN	NaN

Table 2: GPU cluster used for training

Type	Model	Quantity	RAM CPU (G)
GPU	NVIDIA Quattro M5000	1	256
GPU	NVIDIA RTX 2080 Ti	56	384
GPU	NVIDIA RTX 2080 Ti	12	256
GPU	NVIDIA RTX 1080 Ti	6	512
GPU	NVIDIA GTX Titan X	4	128
GPU	NVIDIA GT 640	1	32

D.1 Test Performance on Context Variations

In this section we show the test performance of an agent trained on the default context of selected environments which is oblivious to the context. For evaluation we run 10 episodes on contexts with different magnitudes of variation. We vary each context feature by a magnitude $A = 0.1, 0.2, 0.3, \ldots, 2.2$.

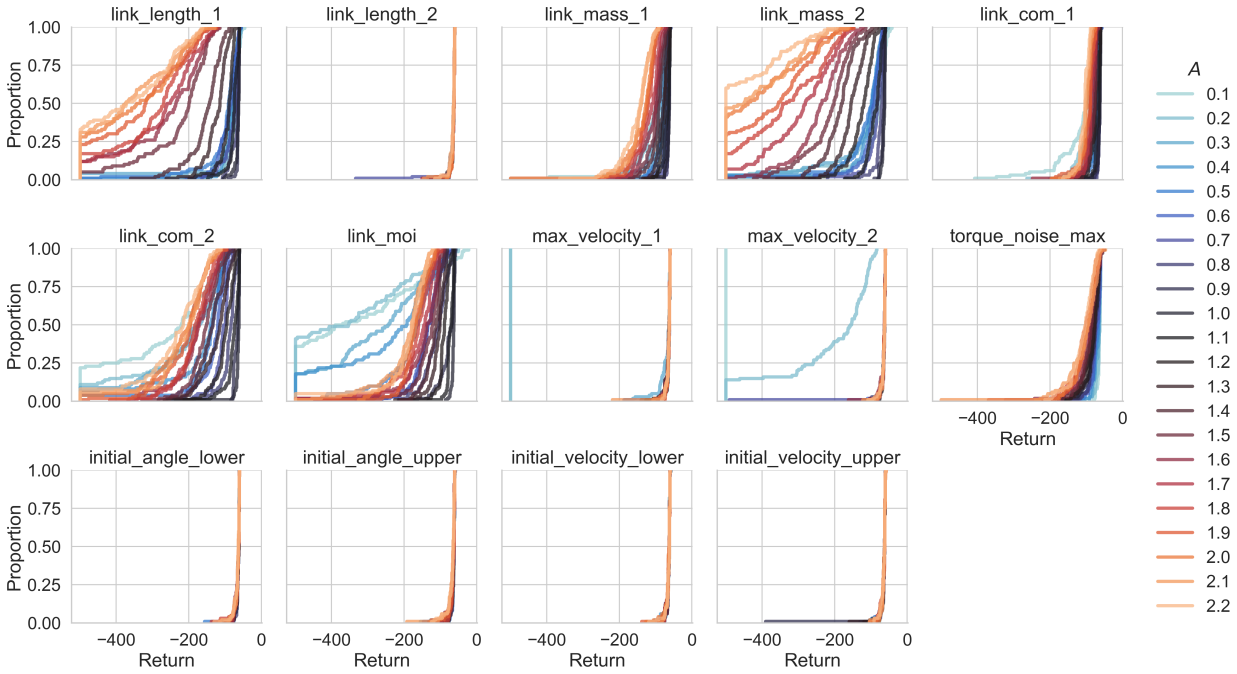


Figure 11: **CARLAcrobotEnv**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

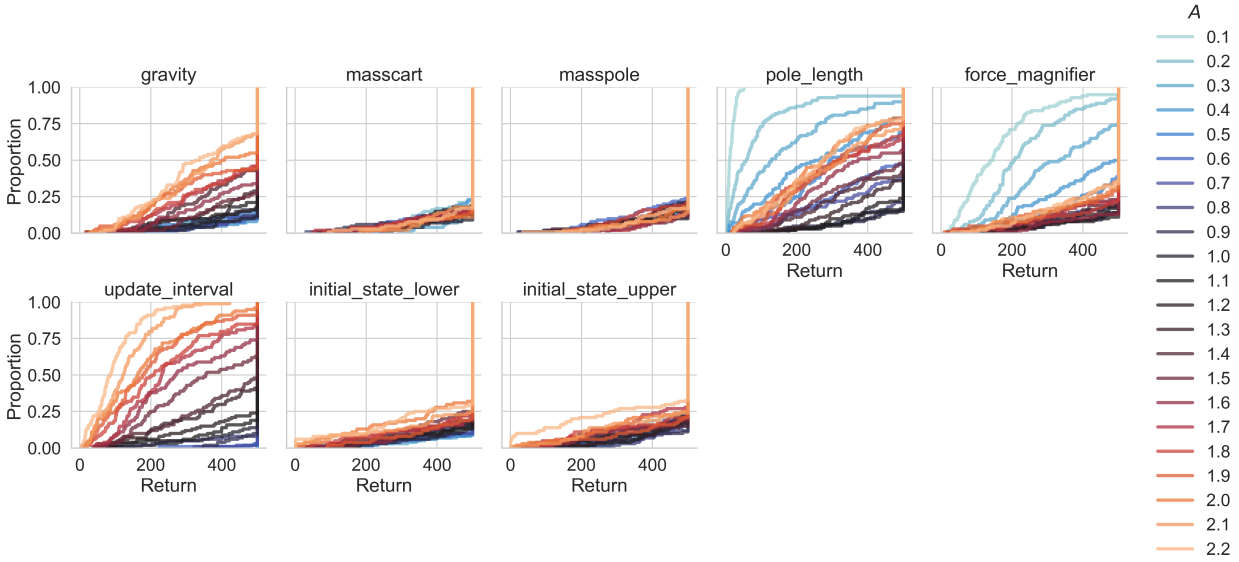


Figure 12: **CARLCartPoleEnv**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

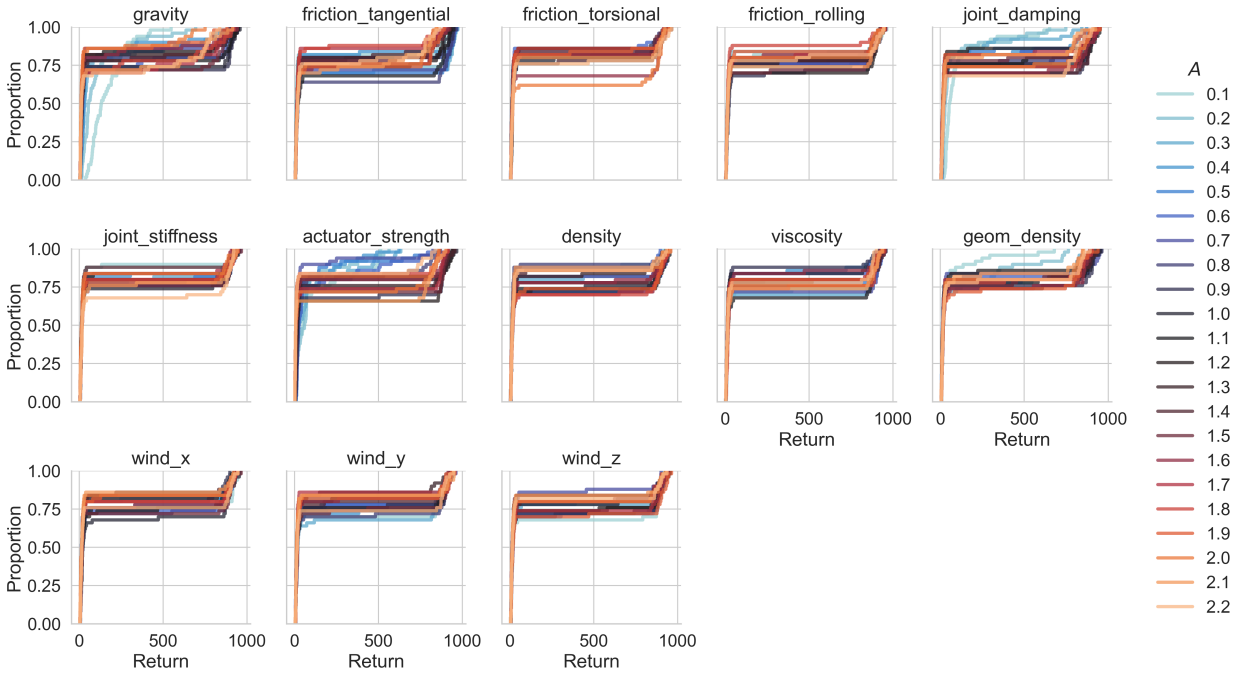


Figure 13: **CARLDmcQuadrupedEnv**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

D.2 Task Variation Through Context

Following the experimental setup in Section 5.1 we conducted further experiments on representative `CARL`-environments.

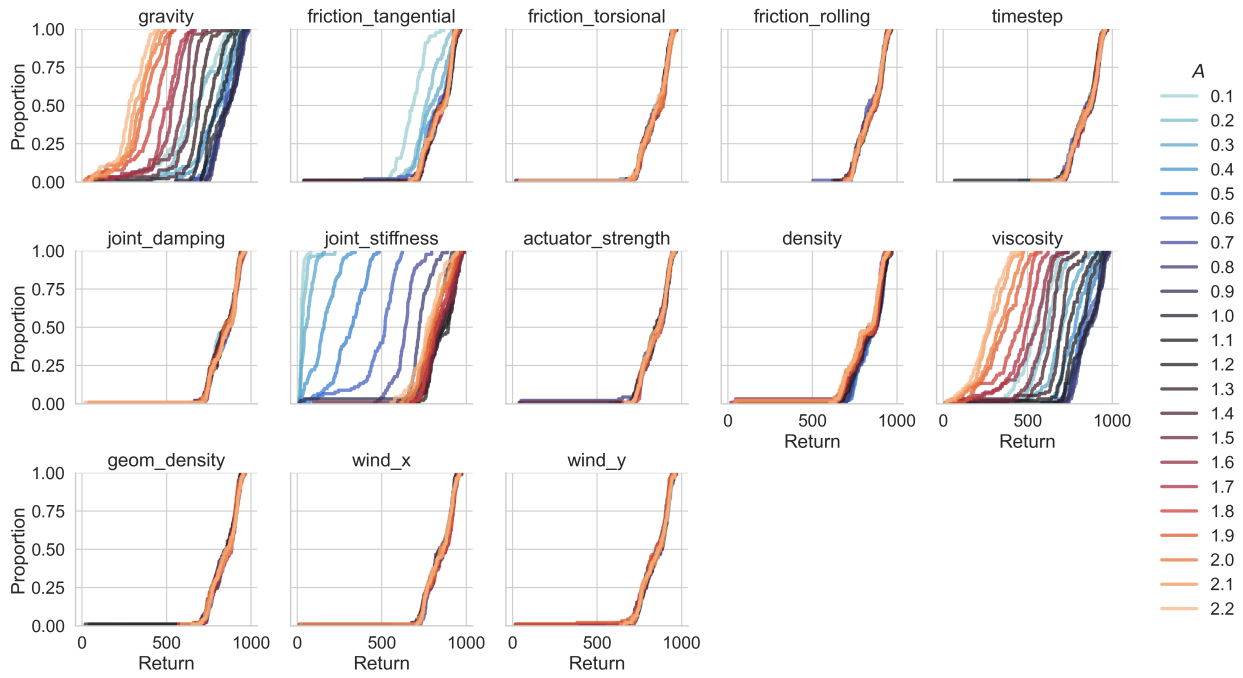


Figure 14: **CARLDmcWalkerEnv**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

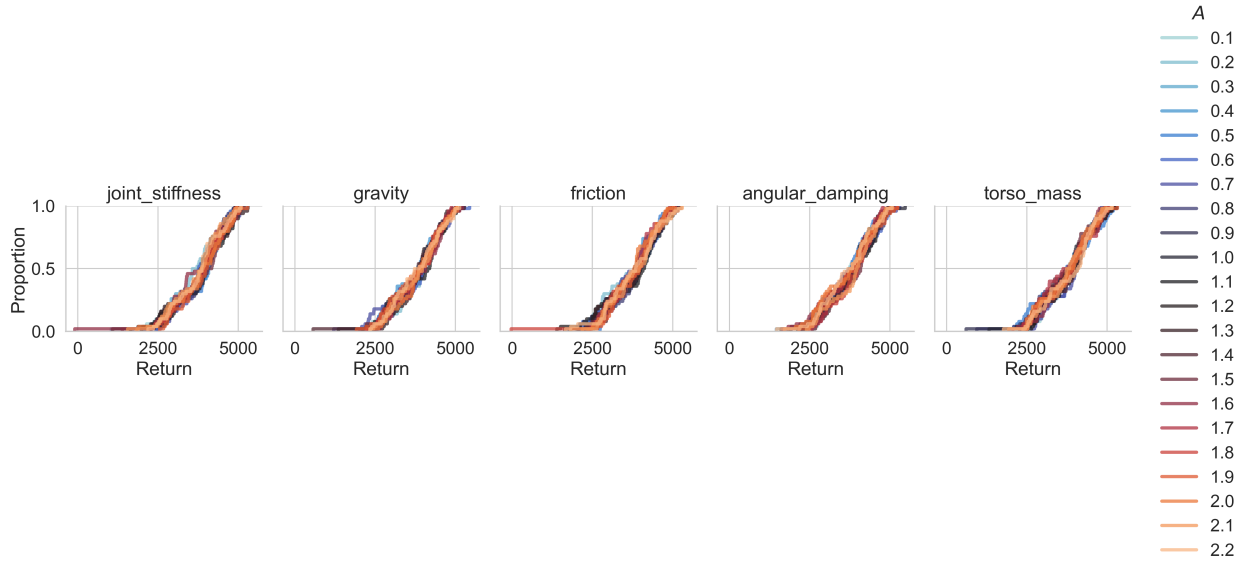


Figure 15: **CARLHalfcheetah**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

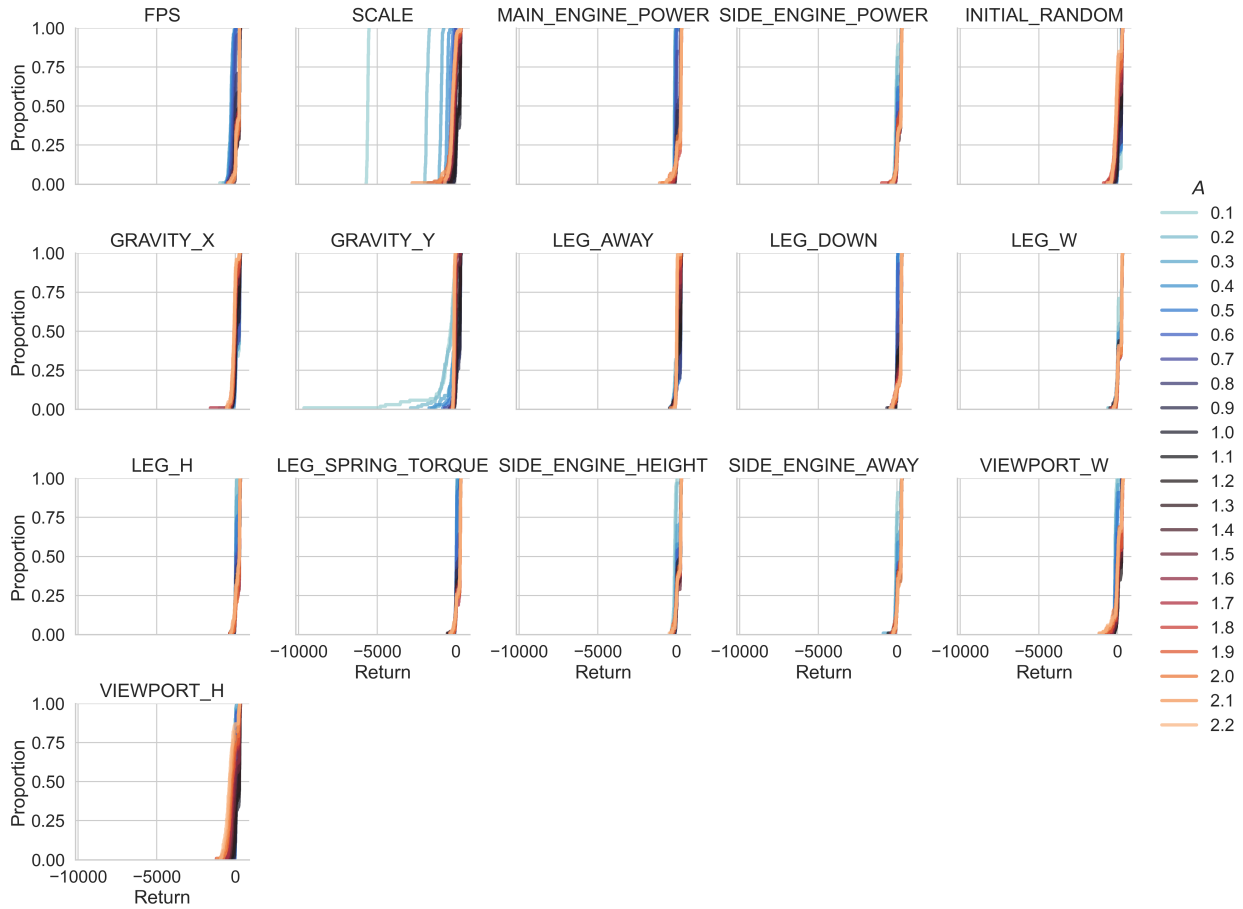


Figure 16: **CARLLunarLanderEnv**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

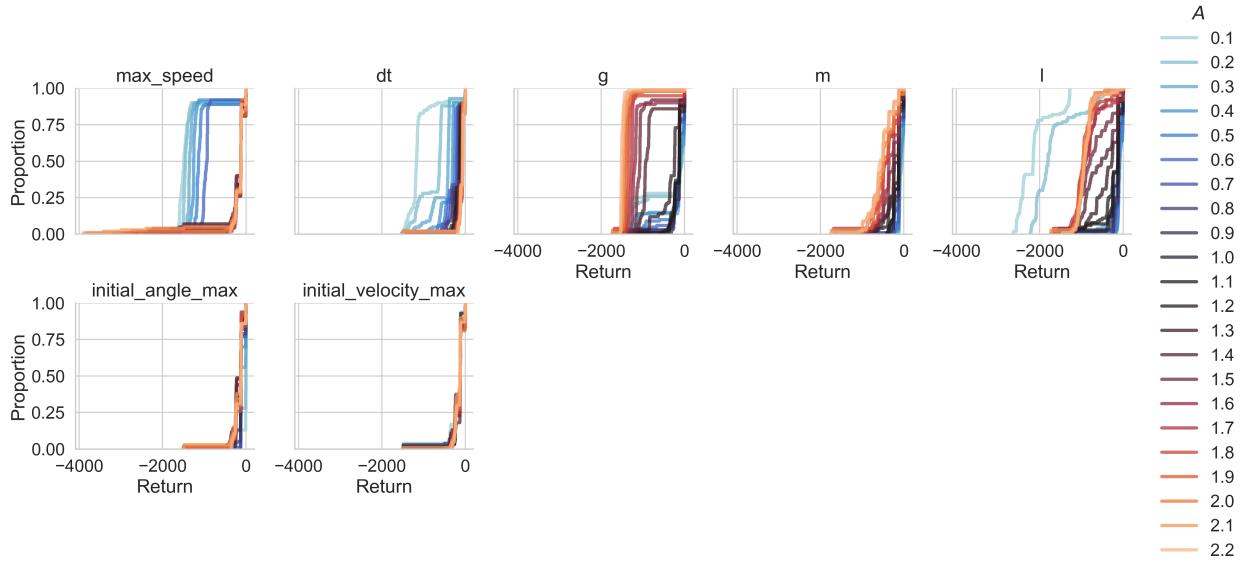
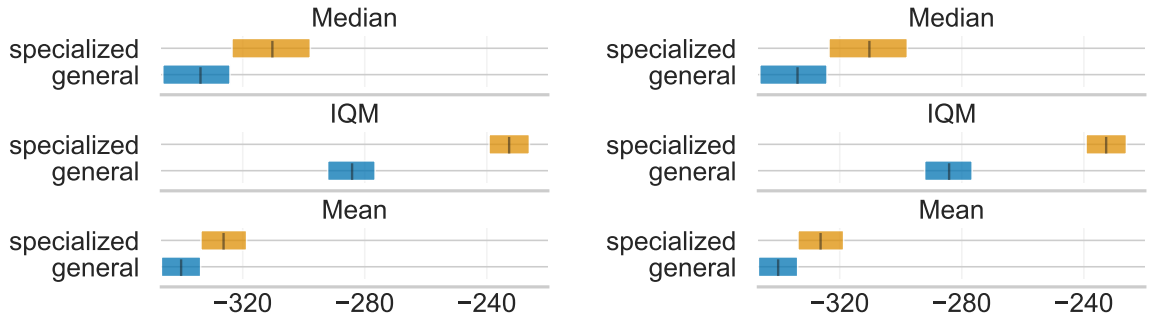


Figure 17: **CARLPendulumEnv**: ECDF Plot. A is the magnitude multiplied with the default value of each context feature.

D.3 Optimality Gap

Here we show the optimality exists for other agent-environment combinations. We repeated the experiment in Section 5.2 with SAC (Haarnoja et al., 2018) on CARLPendulumEnv and CARLDMCWalkerEnv. Both experiments show the optimality gap exists as well, see Figure 18.



(a) CARLPendulumEnv (b) CARLDmcWalkerEnv

Figure 18: Optimality Gap

D.4 Adding Context to the State

When we concatenat all available context features to the observation for CARLPendulum, we often see that the algorithm fails to learn a meaningful policy on some seeds, see Figure 19.

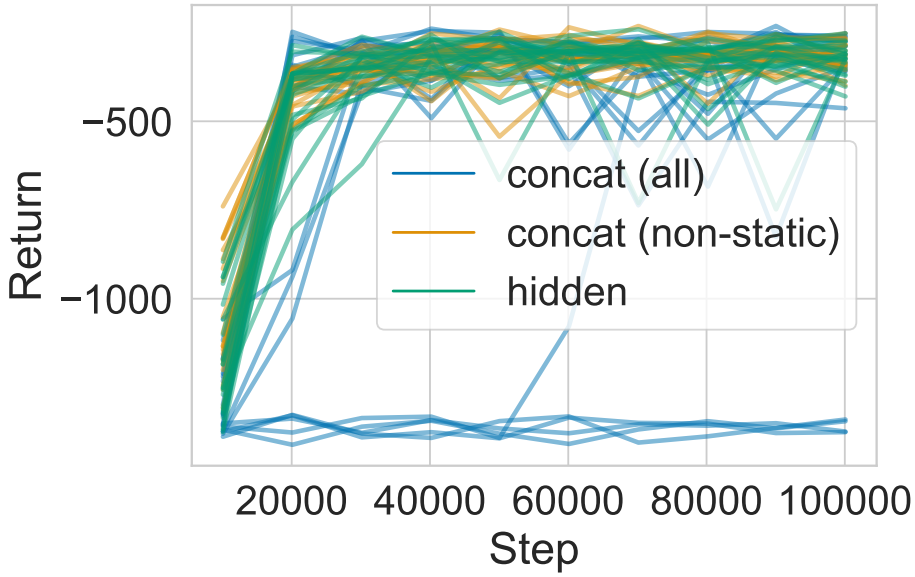


Figure 19: CARLPendulum with different lengths and 20 seeds. Train performance.

D.5 Generalization Results

Here we provide two more combinations for CARLPendulum for the Kirk generalization protocol (Kirk et al., 2021) from Section 5.4 (same experimental setup).

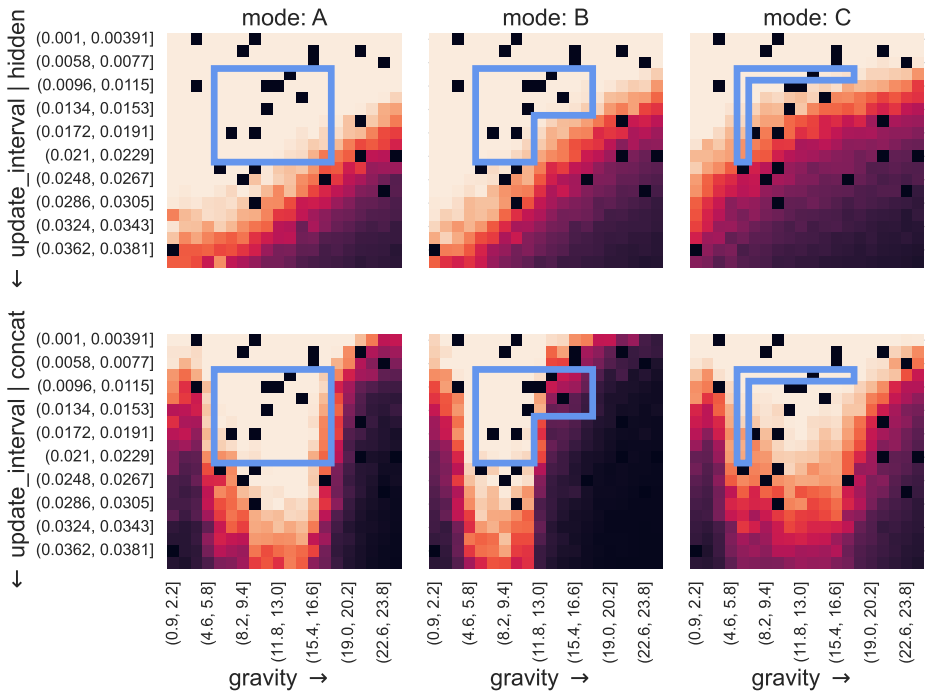


Figure 20: Varying gravity and update interval on CARLPendulumEnv. First row: Hidden agent, second row: Concat agent.

E Hyperparameter Optimization in cRL

We have observed significant differences in learning performance for hidden and full visible context, but the same is also true for hyperparameter tuning in both of these settings. We use the same DQN and DDPG algorithms as in our other experiments with a narrow context distribution of 0.1 for the `CARL` Pendulum, Acrobot and LunarLander environments to show this point. To tune the hyperparameters, we use PB2 (J. Parker-Holder et al., 2020) for the learning rate, target update interval and discount factor.

As shown in Figure 22, the evaluation performances of the found hyperparameter schedules differ significantly in terms of learning speed, stability and results *per environment*. Providing the context sometimes seems to increase the difficulty of the problem (see Section 5.4), i.e. finding a good hyperparameter configuration happens more often and more reliably when the policy is not given the context. We can only speculate on the reasons why this happens, but shows that context introduces complexities to the whole training process beyond simply the policy architecture.

F Open Challenges in cRL

We used the concept of Contextual Reinforcement Learning and its instantiation in `CARL` to demonstrate the usefulness of context information in theory and in practice. More specifically, we showed that making such information about the environment explicitly available to the agent enables faster training and transfer of agents (see Section 5). While this already provides valuable insights to the community that increasingly cares about learning agents capable of generalization (see Sections 1 & 6) Contextual Reinforcement Learning and by extension `CARL` enables to study further open challenges for general RL.

F.1 Challenge I: Representation Learning

Our experiments demonstrated that an agent with access to context information can be capable of learning better than an agent that has to learn behaviors given an implicit context via state observations, but the naive

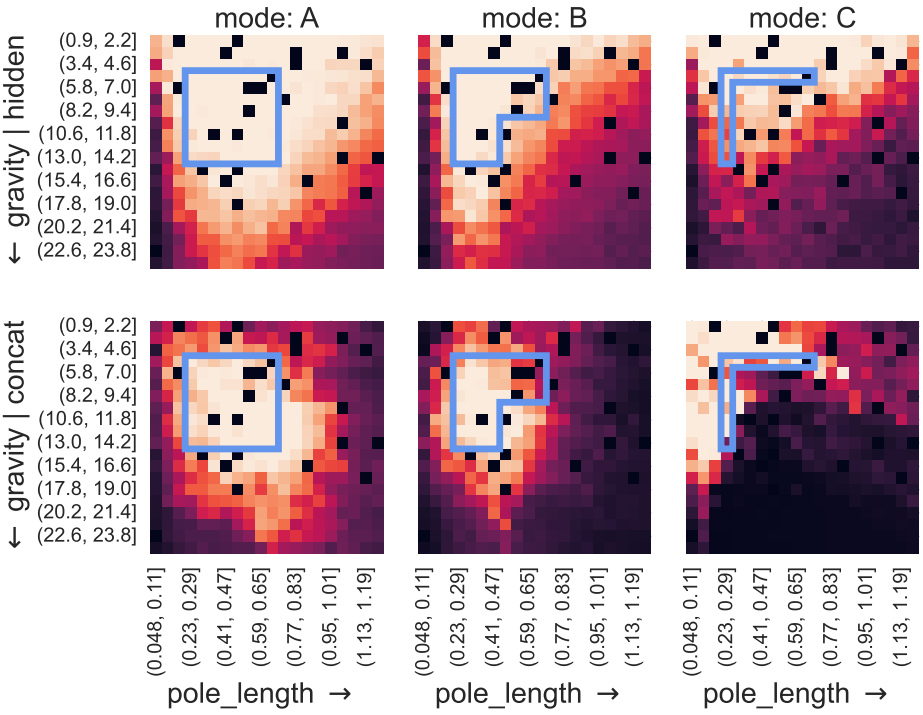
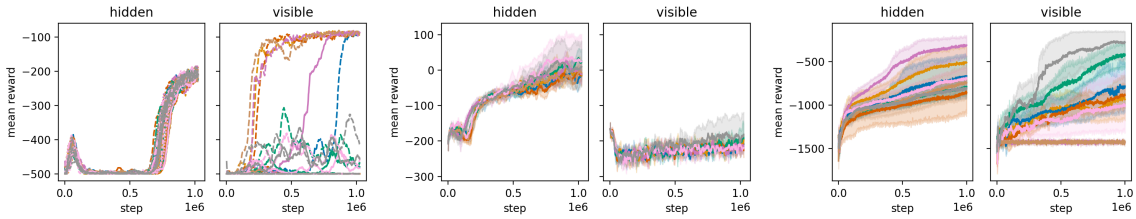


Figure 21: Varying gravity and pole length on CARLPendulumEnv. First row: Hidden agent, second row: Concat agent.



(a) CARLAcrobotEnv (b) CARLLunarLanderEnv (c) CARLPendulumEnv

Figure 22: Hyperparameter Optimization with PB2 (J. Parker-Holder et al., 2020). Hidden means that the context is hidden, and visible means that the full context is appended to the observation.

method of including context information in the observation is not reliable. We theorize that disentangling the representation learning aspect from the policy learning problem reduces complexity. As `CARL` provides ground truth for representations of environment properties we envision future work on principled studies of novel RL algorithms that, by design, disentangle representation learning and policy learning (see, e.g., (Rakelly et al., 2019; Fu et al., 2021a; Zhang et al., 2021b) as first works along this line of research). The ground truth given by the context would allow us to measure the quality of learned representations and allows us to relate this to the true physical properties of an environment.

Another direction of research under the umbrella of representation learning follows the work of environment probing policies (Zhou et al., 2019). There, exploratory policies are learned that allow one to identify which environment type an agent encounters. This is complementary to the prior approaches as representations are not jointly learned with the behaviour policies as in the previously discussed approaches but rather in a separate offline phase. Based on `CARL`, huge amounts of meta-data could be collected that will enable the community to make use of classical meta-algorithmic approaches such as algorithm selection (Rice, 1976) for selecting previously learned policies or learning approaches.

F.2 Challenge II: Uncertainty of RL Agents

With access to context information, we are able to study the influence of noise on RL agents in a novel way. While prior environments enabled studies on the behavior of agents when they could not be certain about their true state in a particular environment, the framework of Contextual Reinforcement Learning further allows studying agents' behaviors in scenarios with uncertainty on their current contextual environment, e.g., because of noise on the context features. In the practical deployment of RL, this is a reasonable concern since context features have to be measured somehow by potentially noisy sensors. As this setting affects the overall transition dynamics, Contextual Reinforcement Learning provides a unique test-bed in which the influence of uncertainty can be studied and how RL agents can deal with such.

F.3 Challenge III: Interpretable and Explainable Deep RL

Trust in the policy is a crucial factor, for which interpretability or explainability often is mandatory. With the provided ground truth through the explicit use of context features, Contextual Reinforcement Learning could be the base for studying the interpretability and explainability of (deep) RL. By enabling AutoRL studies and different representation learning approaches, Contextual Reinforcement Learning will contribute to better interpreting the training procedures.

Contextual Reinforcement Learning further allows studying explainability on the level of learned policies. We propose to study the sensitivity of particular policies to different types of contexts. Thus, the value and variability of a context might serve as a proxy to explain the resulting learned behavior. Such insights might then be used to predict how policies might look or act (e.g., in terms of frequency of action usage) in novel environments, solely based on the provided context features.

F.4 Challenge IV: AutoRL

AutoRL (Parker-Holder et al., 2022) addresses the optimization of the RL learning process. To this end, hyperparameters, architectures or both of agents are adapted either on the fly (Jaderberg et al., 2017a; Franke et al., 2021) or once at the beginning of a run (Runge et al., 2019). However, as AutoRL typically requires large compute resources for this procedure, optimization is most often done only on a per-environment basis. It is reasonable to assume that such hyperparameters might not transfer well to unseen environments, as the learning procedures were not optimized to be robust or to facilitate generalization, but only to improve the reward on a particular instance.

As we have shown above in Appendix E, Contextual Reinforcement Learning provides an even greater challenge for AutoRL methods. On the other hand, as `CARL` provides easy-to-use contextual extensions of a diverse set of RL problems, it could be used to drive research in this open challenge of AutoRL. First of all, it enables a large scale-study to understand how static and dynamic configuration approaches complement each other and when one approach is to be preferred over another. Such a study will most likely also lead to novel default hyperparameter configurations that are more robust and tailored to fast learning and good generalization. In addition, it will open up the possibility to study whether it is reasonable to use a single hyperparameter configuration or whether a mix of configurations for different instances is required (Xu et al., 2010). Furthermore, with the flexibility of defining a broad variety of instance distributions for a large set of provided context features, experiments with `CARL` would allow researchers to study which hyperparameters play a crucial role in learning general agents similar to studies done for supervised machine learning (van Rijn & Hutter, 2018) or AI algorithms (Biedenkapp et al., 2018).

F.5 Challenge V: High Confidence Generalization

The availability of explicit context enables tackling another challenge in the field of safe RL. High Confidence Generalization Algorithms (HCGAs) (Kostas et al., 2021) provide safety guarantees for the generalization of agents in testing environments. Given a worst-case performance bound, the agent can be tasked to decide whether a policy is applicable in an out-of-distribution context or not. This setting is especially important for the deployment of RL algorithms in the real world where policy failures can be costly and the context of

an environment is often prone to change. Contextual Reinforcement Learning has the potential to facilitate the development of HCGAs that base their confidence estimates on the context of an environment.

G Context Features for Each Environment

We list all registered context features with their defaults, bounds and types for each environment family in Table 3 (classic control), Table 4 (box2d), Table 5 (brax) and Table 7 (RNA and Mario).

Table 3: Context Features: Defaults, Bounds and Types for OpenAI gym's Classic Control environments (Brockman et al., 2016)

(a) CARLCartPoleEnv

Context Feature	Default	Bounds	Type
force_magnifier	10.00	(1, 100)	int
gravity	9.80	(0.1, inf)	float
initial_state_lower	-0.10	(-inf, inf)	float
initial_state_upper	0.10	(-inf, inf)	float
masscart	1.00	(0.1, 10)	float
masspole	0.10	(0.01, 1)	float
pole_length	0.50	(0.05, 5)	float
update_interval	0.02	(0.002, 0.2)	float

(b) CARLPendulumEnv

Context Feature	Default	Bounds	Type
dt	0.05	(0, inf)	float
g	10.00	(0, inf)	float
initial_angle_max	3.14	(0, inf)	float
initial_velocity_max	1.00	(0, inf)	float
l	1.00	(1e-06, inf)	float
m	1.00	(1e-06, inf)	float
max_speed	8.00	(-inf, inf)	float

(c) CARLMountainCarEnv

Context Feature	Default	Bounds	Type
force	0.00	(-inf, inf)	float
goal_position	0.50	(-inf, inf)	float
goal_velocity	0.00	(-inf, inf)	float
gravity	0.00	(0, inf)	float
max_position	0.60	(-inf, inf)	float
max_position_start	-0.40	(-inf, inf)	float
max_speed	0.07	(0, inf)	float
max_velocity_start	0.00	(-inf, inf)	float
min_position	-1.20	(-inf, inf)	float
min_position_start	-0.60	(-inf, inf)	float
min_velocity_start	0.00	(-inf, inf)	float

(d) CARLAcrobotEnv

Context Feature	Default	Bounds	Type
initial_angle_lower	-0.10	(-inf, inf)	float
initial_angle_upper	0.10	(-inf, inf)	float
initial_velocity_lower	-0.10	(-inf, inf)	float
initial_velocity_upper	0.10	(-inf, inf)	float
link_com_1	0.50	(0, 1)	float
link_com_2	0.50	(0, 1)	float
link_length_1	1.00	(0.1, 10)	float
link_length_2	1.00	(0.1, 10)	float
link_mass_1	1.00	(0.1, 10)	float
link_mass_2	1.00	(0.1, 10)	float
link_moi	1.00	(0.1, 10)	float
max_velocity_1	12.57	(1.257, 125.7)	float
max_velocity_2	28.27	(2.827, 282.7)	float
torque_noise_max	0.00	(-1.0, 1.0)	float

Table 4: Context Features: Defaults, Bounds and Types for OpenAI gym's Box2d environments (Brockman et al., 2016)

(a) CARLBipedalWalkerEnv

Context Feature	Default	Bounds	Type
FPS	50.00	(1, 500)	float
FRICTION	2.50	(0, 10)	float
GRAVITY_X	0.00	(-20, 20)	float
GRAVITY_Y	-10.00	(-20, -0.01)	float
INITIAL_RANDOM	5.00	(0, 50)	float
LEG_DOWN	-0.27	(-2, -0.25)	float
LEG_H	1.13	(0.25, 2)	float
LEG_W	0.27	(0.25, 0.5)	float
LIDAR_RANGE	5.33	(0.5, 20)	float
MOTORS_TORQUE	80.00	(0, 200)	float
SCALE	30.00	(1, 100)	float
SPEED_HIP	4.00	(1e-06, 15)	float
SPEED_KNEE	6.00	(1e-06, 15)	float
TERRAIN_GRASS	10.00	(5, 15)	int
TERRAIN_HEIGHT	5.00	(3, 10)	float
TERRAIN_LENGTH	200.00	(100, 500)	int
TERRAIN_STARTPAD	20.00	(10, 30)	int
TERRAIN_STEP	0.47	(0.25, 1)	float
VIEWPORT_H	400.00	(200, 800)	int
VIEWPORT_W	600.00	(400, 1000)	int

(b) CARLLunarLanderEnv

Context Feature	Default	Bounds	Type
FPS	50.00	(1, 500)	float
GRAVITY_X	0.00	(-20, 20)	float
GRAVITY_Y	-10.00	(-20, -0.01)	float
INITIAL_RANDOM	1000.00	(0, 2000)	float
LEG_AWAY	20.00	(0, 50)	float
LEG_DOWN	18.00	(0, 50)	float
LEG_H	8.00	(1, 20)	float
LEG_SPRING_TORQUE	40.00	(0, 100)	float
LEG_W	2.00	(1, 10)	float
MAIN_ENGINE_POWER	13.00	(0, 50)	float
SCALE	30.00	(1, 100)	float
SIDE_ENGINE_AWAY	12.00	(1, 20)	float
SIDE_ENGINE_HEIGHT	14.00	(1, 20)	float
SIDE_ENGINE_POWER	0.60	(0, 50)	float
VIEWPORT_H	400.00	(200, 800)	int
VIEWPORT_W	600.00	(400, 1000)	int

(c) CARLVehicleRacingEnv

Context Feature	Default	Bounds	Type
VEHICLE	0	-	categorical

Table 5: Context Features: Defaults, Bounds and Types for Google Brax environments (Freeman et al., 2021)

(a) CARLAnt

Context Feature	Default	Bounds	Type
actuator_strength	300.00	(1, inf)	float
angular_damping	-0.05	(-inf, inf)	float
friction	0.60	(-inf, inf)	float
gravity	-9.80	(-inf, -0.1)	float
joint_angular_damping	35.00	(0, inf)	float
joint_stiffness	5000.00	(1, inf)	float
torso_mass	10.00	(0.1, inf)	float

(b) CARLHalfcheetah

Context Feature	Default	Bounds	Type
angular_damping	-0.05	(-inf, inf)	float
friction	0.60	(-inf, inf)	float
gravity	-9.80	(-inf, -0.1)	float
joint_angular_damping	20.00	(0, inf)	float
joint_stiffness	15000.00	(1, inf)	float
torso_mass	9.46	(0.1, inf)	float

(c) CARLFetch

Context Feature	Default	Bounds	Type
actuator_strength	300.00	(1, inf)	float
angular_damping	-0.05	(-inf, inf)	float
friction	0.60	(-inf, inf)	float
gravity	-9.80	(-inf, -0.1)	float
joint_angular_damping	35.00	(0, inf)	float
joint_stiffness	5000.00	(1, inf)	float
target_distance	15.00	(0.1, inf)	float
target_radius	2.00	(0.1, inf)	float
torso_mass	1.00	(0.1, inf)	float

(d) CARLGrasp

Context Feature	Default	Bounds	Type
actuator_strength	300.00	(1, inf)	float
angular_damping	-0.05	(-inf, inf)	float
friction	0.60	(-inf, inf)	float
gravity	-9.80	(-inf, -0.1)	float
joint_angular_damping	50.00	(0, inf)	float
joint_stiffness	5000.00	(1, inf)	float
target_distance	10.00	(0.1, inf)	float
target_height	8.00	(0.1, inf)	float
target_radius	1.10	(0.1, inf)	float

(e) CARLHumanoid

Context Feature	Default	Bounds	Type
angular_damping	-0.05	(-inf, inf)	float
friction	0.60	(-inf, inf)	float
gravity	-9.80	(-inf, -0.1)	float
joint_angular_damping	20.00	(0, inf)	float
torso_mass	8.91	(0.1, inf)	float

(f) CARLUr5e

Context Feature	Default	Bounds	Type
actuator_strength	100.00	(1, inf)	float
angular_damping	-0.05	(-inf, inf)	float
friction	0.60	(-inf, inf)	float
gravity	-9.81	(-inf, -0.1)	float
joint_angular_damping	50.00	(0, 360)	float
joint_stiffness	40000.00	(1, inf)	float
target_distance	0.50	(0.01, inf)	float
target_radius	0.02	(0.01, inf)	float
torso_mass	1.00	(0, inf)	float

Table 6: Context Features: Defaults, Bounds and Types for Google Deepmind environments (Tassa et al., 2018)

(a) CARLDmcWalkerEnv

Context Feature	Default	Bounds	Type
actuator_strength	1.00	(0, inf)	float
density	0.00	(0, inf)	float
friction_rolling	1.00	(0, inf)	float
friction_tangential	1.00	(0, inf)	float
friction_torsional	1.00	(0, inf)	float
geom_density	1.00	(0, inf)	float
gravity	-9.81	(-inf, -0.1)	float
joint_damping	1.00	(0, inf)	float
joint_stiffness	0.00	(0, inf)	float
timestep	0.00	(0.001, 0.1)	float
viscosity	0.00	(0, inf)	float
wind_x	0.00	(-inf, inf)	float
wind_y	0.00	(-inf, inf)	float
wind_z	0.00	(-inf, inf)	float

(b) CARLDmcQuadrupedEnv

Context Feature	Default	Bounds	Type
actuator_strength	1.00	(0, inf)	float
density	0.00	(0, inf)	float
friction_rolling	1.00	(0, inf)	float
friction_tangential	1.00	(0, inf)	float
friction_torsional	1.00	(0, inf)	float
geom_density	1.00	(0, inf)	float
gravity	-9.81	(-inf, -0.1)	float
joint_damping	1.00	(0, inf)	float
joint_stiffness	0.00	(0, inf)	float
timestep	0.01	(0.001, 0.1)	float
viscosity	0.00	(0, inf)	float
wind_x	0.00	(-inf, inf)	float
wind_y	0.00	(-inf, inf)	float
wind_z	0.00	(-inf, inf)	float

(c) CARLDmcFingerEnv

Context Feature	Default	Bounds	Type
actuator_strength	1.00	(0, inf)	float
density	5000.00	(0, inf)	float
friction_rolling	1.00	(0, inf)	float
friction_tangential	1.00	(0, inf)	float
friction_torsional	1.00	(0, inf)	float
geom_density	1.00	(0, inf)	float
gravity	-9.81	(-inf, -0.1)	float
joint_damping	1.00	(0, inf)	float
joint_stiffness	0.00	(0, inf)	float
limb_length_0	0.17	(0.01, 0.2)	float
limb_length_1	0.16	(0.01, 0.2)	float
spinner_length	0.18	(0.01, 0.4)	float
spinner_radius	0.04	(0.01, 0.05)	float
timestep	0.00	(0.001, 0.1)	float
viscosity	0.00	(0, inf)	float
wind_x	0.00	(-inf, inf)	float
wind_y	0.00	(-inf, inf)	float
wind_z	0.00	(-inf, inf)	float

(d) CARLDmcFishEnv

Context Feature	Default	Bounds	Type
actuator_strength	1.00	(0, inf)	float
density	5000.00	(0, inf)	float
friction_rolling	1.00	(0, inf)	float
friction_tangential	1.00	(0, inf)	float
friction_torsional	1.00	(0, inf)	float
geom_density	1.00	(0, inf)	float
gravity	-9.81	(-inf, -0.1)	float
joint_damping	1.00	(0, inf)	float
joint_stiffness	0.00	(0, inf)	float
timestep	0.00	(0.001, 0.1)	float
viscosity	0.00	(0, inf)	float
wind_x	0.00	(-inf, inf)	float
wind_y	0.00	(-inf, inf)	float
wind_z	0.00	(-inf, inf)	float

Table 7: Context Features: Defaults, Bounds and Types for RNA Design (Runge et al., 2019) and Mario Environment (Awiszus et al., 2020; Schubert et al., 2021)

(a) CARLRnaDesignEnv

Context Feature	Default	Bounds	Type
mutation_threshold	5	(0.1, inf)	float
reward_exponent	1	(0.1, inf)	float
state_radius	5	(1, inf)	float
dataset	eterna	-	categorical, $n = 3$
target_structure_ids	f(dataset)	(0, inf)	list of int

(b) CARLMarioEnv

Context Feature	Default	Bounds	Type
level_index	0	-	categorical, $n = 15$
noise	f(level_index, width, height)	(-1, 1)	float
mario_state	0	-	categorical, $n = 3$
mario_inertia	0.89	(0.5, 1.5)	float