# Structure in Reinforcement Learning: A Survey and Open Problems

Aditya Mohan

A.MOHAN@AI.UNI-HANNOVER.DE

Institute of Artificial Intelligence Leibniz University Hannover

Amy Zhang
University of Texas at Austin, Meta AI

Marius Lindauer

M.LINDAUER@AI.UNI-HANNOVER.DE

AMY.ZHANG@AUSTIN.UTEXAS.EDU

Institute of Artificial Intelligence Leibniz University Hannover

## Abstract

Reinforcement Learning (RL), bolstered by the expressive capabilities of Deep Neural Networks (DNNs) for function approximation, has demonstrated considerable success in numerous applications. However, its practicality in addressing various real-world scenarios, characterized by diverse and unpredictable dynamics, noisy signals, and large state and action spaces, remains limited. This limitation stems from issues such as poor data efficiency, limited generalization capabilities, a lack of safety guarantees, and the absence of interpretability, among other factors. To overcome these challenges and improve performance across these crucial metrics, one promising avenue is to incorporate additional structural information about the problem into the RL learning process. Various sub-fields of RL have proposed methods for incorporating such inductive biases. We amalgamate these diverse methodologies under a unified framework, shedding light on the role of structure in the learning problem, and classify these methods into distinct patterns of incorporating structure. By leveraging this comprehensive framework, we provide valuable insights into the challenges of structured RL and lay the groundwork for a design pattern perspective on RL research. This novel perspective paves the way for future advancements and aids in developing more effective and efficient RL algorithms that can potentially handle real-world scenarios better.

## 1. Introduction

Reinforcement Learning (RL) has contributed to a range of sequential decision-making and control problems like games (Silver et al., 2016), robotic manipulation (Lee et al., 2020b), optimizing chemical reactions (Zhou et al., 2017), and RNA folding (Whatley et al., 2021). Most of the traditional research in RL focuses on designing agents that learn to solve a sequential decision problem induced by the inherent dynamics of a task, e.g., the differential equations governing the cart pole task in the classic control suite (Sutton & Barto, 2018; Brockman et al., 2016). However, their performance significantly degrades when even small aspects of the environment change (Meng & Khushi, 2019; Lu et al., 2020). Moreover, deploying RL agents for real-world learning-based optimization has additional challenges, such as complicated dynamics, intractable and computationally expensive state and action spaces, and noisy reward signals.

Thus, research in RL has started to address these issues through methods that can generally be categorized into two dogmas (Mannor & Tamar, 2023): (i) Generalization: Methods developed to solve a broader class of problems where the agent is trained on various tasks and environments (Kirk et al., 2023; Benjamins et al., 2023). (ii) Deployability: Methods that are specifically engineered towards concrete real-world problems by incorporating additional aspects such as feature engineering, computational budget optimization, safety, etc. The intersection of generalization and deployability is particularly interesting since it covers a class of problems where we require methods to handle sufficient diversity in the task while being deployable for specific applications. To foster research in this area, Mannor and Tamar (2023) argue for a design-pattern oriented approach, where methods can be abstracted into patterns that are specialized to specific kinds of problems.

However, the path to RL design patterns is hindered by gaps in our understanding of the relationship between the design decisions for RL methods and the properties of the problems they might be suited for. While decisions like using state abstractions for high-dimensional spaces seem obvious, decisions like using relational neural architectures for problems are not so obvious to a designer. One way to add principle to this process is to understand how to incorporate additional domain knowledge into the learning pipeline. A strong source of such domain knowledge is the structure present in the learning problem itself, including priors about the state space, the action space, the reward function, or the dynamics of the environment. While such methods have been research subjects throughout the history of RL (Parr & Russell, 1997), approaches for doing so in Deep RL are scattered across the various sub-fields in the vast and disparate landscape of modern RL research.

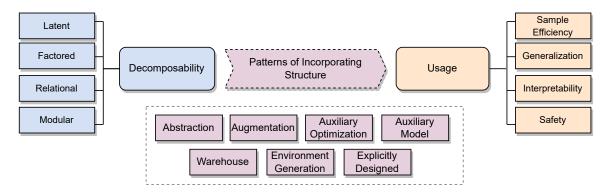


Figure 1: **Overview of our framework.** Domain knowledge can generally be incorporated into an RL pipeline as side information and can be used to achieve improved performance across metrics such as *Sample Efficiency*, *Generalization*, *Interpretability*, and *Safety*. We discuss this process in Section 3. A particular source of side information is decomposability in a learning problem, which can be categorized into four archetypes along a spectrum - *Latent*, *Factored*, *Relational*, and *Modular* - explained further in Section 4.1. Incorporating side information about decomposability amounts to adding structure to a learning pipeline, and this process can be categorized into seven different patterns - *Abstraction*, *Augmentation*, *Auxiliary Optimization*, *Auxiliary Model*, *Warehouse*, *Environment Generation*, and *Explicitly Designed* - discussed further in Section 5.

Contributions and Structure of the Paper. In this work, we take the first steps in amalgamating these approaches under our pattern-centric framework for incorporating structure in RL. Figure 1 shows a general overview of three elements of understanding the role of incorporating structure into a learning problem that we cover in this work. In Section 2, we describe the background and notation needed to formalize the relevant aspects of the RL problems. In Section 3, we introduce the notion of side information and define different additional metrics that can be addressed by incorporating side information into an RL pipeline. We then formulate structure as a particular kind of side information about decomposability in a problem in Section 4, and categorize decompositions in the literature into four major archetypes. In Section 5, we formulate seven patterns of incorporating structure into the RL learning process and provide an overview of each pattern by connecting it to the relevant surveyed literature. The framework developed in this work opens new avenues for research while providing a common reference point for understanding what kind of design decisions work under which situations. We discuss these aspects further in Section 6 for more concrete takeaways for researchers and practitioners.

#### 2. Preliminaries

The following sections summarize the main background necessary for our approach to studying structural decompositions and related patterns. In Section 2.1, we formalize the sequential decision-making problem as an MDP. Section 2.2 then presents the RL framework for solving MDPs and introduces the RL pipeline.

## 2.1 Markov Decision Processes

Sequential decision-making problems are usually formalized using the notion of a Markov Decision Process (MDP) (Bellman, 1954; Puterman, 2014), which can be written down as a 5-tuple  $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, R, P, \rho \rangle$ . At any timestep, the environment exists in a state  $s \in \mathcal{S}$ , with  $\rho$  being the initial state distribution. The agent takes an action  $a \in \mathcal{A}$  which transitions the environment to a new state  $s' \in \mathcal{S}$ . The stochastic transition function governs the dynamics of such transitions  $P: \mathcal{S} \times \mathcal{A} \to \Delta(\mathcal{S})$ , which takes the state s and action s as input and outputs a probability distribution over the next states s. If the next state s can be sampled. For each transition, the agent receives a reward s and s and s and s are s and s and s are s are s and s are s and s are s and s are s and s are s and s are s are s are s and s are s are s and s are s and s are s and s are s and s are s are s and s are s are s and s are s are s and s are s are s are s are s and s are s are

The agent acts according to a policy  $\pi: \mathcal{S} \to \Delta(\mathcal{A})$ , in a space of policies  $\Pi$ , that produces a probability distribution over actions given a state. This distribution is a delta distribution for deterministic policies, which leads to the policy outputting a single action. Using the current policy, an agent can repeatedly generate experiences, and a sequence of such experiences is also called a trajectory ( $\tau$ ). In episodic RL, the trajectory consists of experiences collected over multiple episodes with environment resets, while in continual settings, the trajectory encompasses experiences collected over some horizon in a single episode. The rewards in  $\tau$  can be accumulated into an expected sum called the return G, which can be calculated for any starting state s as

$$G(\pi, s) = \mathbb{E}_{(s_0 = s, a_1, r_1, \dots) \sim \mathcal{M}} \left[ \sum_{t=0}^{\infty} r_t \right]. \tag{1}$$

For the sum in Equation (1) to be tractable, we either assume the horizon of the problem to be of a fixed length T (finite-horizon return), i.e., the trajectory to terminate after T-steps, or we discount the future rewards by a discount factor  $\gamma$  (infinite horizon return). Discounting, however, can also be applied to finite horizons. Solving an MDP amounts to determining the policy  $\pi^* \in \Pi$  that maximizes the expectation over the returns of its trajectory. This expectation can be captured by the notion of the (state-action) value function  $Q \in \mathcal{Q}$ . Given a policy  $\pi$ , the expectation can be written recursively:

$$Q^{\pi}(s, a) = \mathbb{E}_{s \sim \rho} [G_t \mid s, a] = \mathbb{E}_{s' \sim \tau} [R(s, a) + \gamma \mathbb{E}_{a' \sim \pi(\cdot \mid s')} [Q^{\pi}(s', a')]]. \tag{2}$$

Thus, the goal can now be formulated as the task of finding an optimal policy that can maximize the  $Q^{\pi}(s, a)$ :

$$\pi^* \in \operatorname*{arg\,max}_{\pi \in \Pi} Q^{\pi}(s, a). \tag{3}$$

We also consider partially observable MDPs (POMDPs), which model situations where the state is not fully observable. A POMDP is defined as a 7-tuple  $\mathcal{M} = \langle \mathcal{S}, \mathcal{A}, \mathcal{O}, R, P, \xi, \rho \rangle$ , where  $\mathcal{S}, \mathcal{A}, R, P, \rho$  remain the same as defined above. Instead of observing the state  $s \in \mathcal{S}$ , the agent now has access to observation  $o \in \mathcal{O}$  that is generated from the true state through an emission function  $\xi : \mathcal{S} \to \mathcal{O}$ . Thus, the observation takes the state's role in the experience generation process, and the rest of the learning process can now be conditioned on o instead of s.

## 2.2 Reinforcement Learning

The task of an RL algorithm is to interact with the MDP by simulating its transition dynamics  $P(s' \mid s, a)$  and reward function R(s, a) and learn the optimal policy mentioned in Equation (3). In Deep RL, the policy is a Deep Neural Network (Goodfellow et al., 2016) that is used to generate  $\tau$ . We can optimize such a policy by minimizing an appropriate objective  $J \in \mathcal{J}$ .

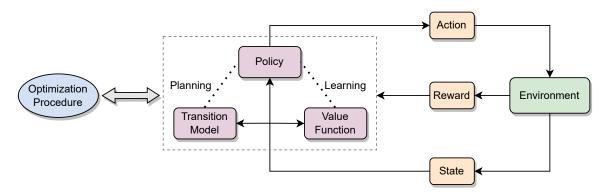


Figure 2: The anatomy of an RL pipeline.

A model of an MDP  $\hat{\mathcal{M}}$  allows an agent to *plan* a trajectory by simulating it to generate experiences. RL methods that use such models are categorized into *Model-Based RL* (Moerland et al., 2023). On the other hand, not having such a model necessitates learning the policy directly from experiences, and such methods fall into the category of *Model-free RL*.

RL methods can additionally be categorized based on the type of objective J. Methods that use a value function, and correspondingly the Temporal Difference error (Sutton, 1988), to learn a policy fall into the category of Value-based RL. A key idea in these methods is bootstrapping, where they use a learned value estimate to improve the estimate of a state that precedes it. On-policy methods directly update the policy that generated the experiences, while Off-policy methods use a separate policy to generate experiences. Policy-Based Methods parameterize the policy directly and use the Policy Gradient (Williams, 1992a; Sutton et al., 1999a) to create J.

A central research theme in practical RL methods focuses on approximating a global solution by iteratively learning one or more of the aforementioned quantities using supervised learning and function approximations. We use the notion of a pipeline to talk about different RL methods. Figure 2 shows the anatomy of an RL pipeline. The pipeline can be defined as a mathematical tuple  $\Omega = \langle \mathcal{S}, \mathcal{A}, R, P, Q, \pi, \hat{\mathcal{M}}, J, \mathcal{E} \rangle$ , where all definitions remain the same as before. To solve an MDP, the pipeline operates on given an environment  $\mathcal{E}$  by taking the state  $s \in \mathcal{S}$  as input and producing an action  $a \in \mathcal{A}$  as an output. The environment operates with the dynamics P and a reward function R. The pipeline might generate experiences by directly interacting with  $\mathcal{E}$ , i.e., learning from experiences or by simulating a learned model  $\hat{\mathcal{M}}$  of the environment. The optimization procedure encompasses the interplay between the current policy  $\pi$ , its value function Q, the reward R, and the learning objective J. With a slight abuse of notation, we refer to any of the components of a pipeline as X and assume the space in which it exists as  $\mathcal{X}$ .

#### 3. Side Information and its Usage

In addition to the characterization of the problem by an MDP, there can still be additional information that could potentially improve performance on additional metrics such as Sample Efficiency, Generalization, Interpretability, and Safety. We call this Side Information (also referred to as privileged information). For the (semi-) supervised and unsupervised settings, side information is any additional information  $z \in \mathcal{Z}$  that, while being neither part of the input nor the output space, can potentially contribute to the learning process (Jonschkowski et al., 2015).

Translated to the RL setting, this can be understood as additional information z not provided in the original MDP definition  $\mathcal{M}$ . Such information can be incorporated into the learning process by a function  $\beta: \mathcal{Z} \to \mathcal{X}$ , where  $\mathcal{X} \in \Omega$ . Thus, side information can be incorporated into the RL pipeline by biasing one or more of the components shown in Figure 2.

The natural follow-up question, then, becomes the impact of incorporating side information into the learning pipeline. In this work, we specifically focus on four ways in which side information can be used and formally define them in the following sections.

# 3.1 Sample Efficiency

Sample Efficiency is intimately tied to the idea of the Sample Complexity of RL. To formally define it, we use the notion of the Sample Complexity of Exploration (Kakade, 2003): Given fixed parameters  $\epsilon, \delta > 0$ , if the difference between the value functions of a learned policy  $\pi$  and an optimal policy  $\pi^*$  is  $||Q^{\pi}(s,a) - Q^{\star}(s,a)||_{\infty} > \epsilon$ , then we call this a mistake. If, with a probability of  $1 - \delta$ , the total number of mistakes at a timestep t is  $\zeta(\epsilon, \delta)$ , then we call  $\zeta$  the sample complexity of exploration.

Incorporating side information leads to a reduction in  $\zeta$ , thus, improving the sample efficiency. Intuitively, if a pipeline demonstrates a higher reward than a baseline for the same number of timesteps, then we consider it more sample efficient. However, methods can additionally make specific claims on  $\zeta$  by utilizing certain assumptions about the problem itself (D'Eramo et al., 2020; Modi et al., 2018; Brunskill & Li, 2013).

Exploration. One specific way to improve the sample complexity of exploration is to impact the exploration mechanism using side information directly. Amin et al. (2021b) categorize exploration methods based on the type of information that an agent uses to explore the world into the following categories: (i) Reward-Free Exploration methods in which extrinsic rewards do not affect the choice of action. Instead, they rely on intrinsic forms of exploration. (ii) Randomized Action Selection methods use estimated value functions, policies, or rewards to induce exploratory behavior. (iii) Optimism/Bonus-Based Exploration methods use the optimism in the face of uncertainty paradigm to prefer actions with higher uncertain values. (iv) Deliberate Exploration methods that either use posterior distributions over dynamics (Bayesian setup) or meta-learning techniques to optimally solve exploration and (v) Probability Matching methods that use heuristics to select the next action. Incorporating side information into any of these methods generally leads to better sample efficiency, particularly by improving the state-space coverage of the exploration mechanism.

#### 3.2 Transfer and Generalization

Transfer and generalization encompass performance metrics that measure how an RL agent performs on a set of different MDPs: Transfer evaluates how well an agent, trained on some MDP  $\mathcal{M}_i$  performs on some other MDP  $\mathcal{M}_j$ . This can be either done in a zero-shot manner, where the agent is not fine-tuned on  $\mathcal{M}_j$ , or in a few-shot manner, where the agent gets to make some policy updates on  $\mathcal{M}_j$  to learn as fast as possible. Generally, the performance gap between the two MDPs determines the transfer performance.

$$J_{\text{transfer}}(\pi) := \mathbf{G}(\pi, \mathcal{M}_i) - \mathbf{G}(\pi, \mathcal{M}_j). \tag{4}$$

Generalization extends this idea to training an agent on a set of training MDPs  $\mathcal{M}_{train}$ , and then evaluating its performance on a separate set of MDPs  $\mathcal{M}_{test}$ . Consequently, generalization (Kirk et al., 2023) can then be measured by the metric.

$$Gen(\pi) := G(\pi, \mathcal{M}_{train}) - G(\pi, \mathcal{M}_{test}). \tag{5}$$

A more restrictive form of generalization can be evaluated when the training and testing MDPs are sampled from the same distribution, i.e.,  $\mathcal{M}_{train}$ ,  $\mathcal{M}_{test} \sim p(\mathcal{M})$ . Depending on

how the transfer is done (zero-shot, few-shot, etc.), this notion covers any form of distribution of MDPs, including multi-task settings. Incorporating side information into the learning can minimize  $Gen(\pi)$  by capturing similarities between  $\mathcal{M}_{train}$  and  $\mathcal{M}_{test}$  in many different ways.

## 3.3 Interpretability

Interpretability refers to a mechanistic understanding of a system to make it more transparent. Lipton (2018) enumerate three fundamental properties of model interpretability: (i) **Simulatability** refers to the ability of a human to simulate the inner working of a system, (ii) **Decomposability** refers to adding intuitive understanding to individual working parts of a system, (iii) **Transparency** refers to improving the understanding of a system's function (e.g., quantifying its convergence properties).

Given the coupled nature of individual parts of an RL pipeline, adding interpretability amounts to being able to learn a policy for the MDP that adheres to one of multiple such properties. Incorporating side information can help take steps towards improved performance on all three of these metrics, depending on the nature of side information and what it encompasses. We consider claims on interpretability based on whether a given work additionally addresses at least two of these metrics.

## 3.4 Safety

Safety is the idea of learning policies that maximize the expectation of the return in problems in which it is important to ensure reasonable system performance and respect safety constraints during the learning and or deployment processes.

While Safety in RL is a vast field in and of itself (Garcia & Fernandez, 2015), we consider two specific categories in this work: Safe Learning with constraints and Safe Exploration. The former modifies the expected return account for one or more constraints  $c_i \in C$ , and the general form can be written as

$$\max_{\pi \in \Pi} \mathbb{E}_{\pi}(G) \ s.t. \ c_i = \{ h_i \le \alpha \}$$
 (6)

where  $h_i$  is a function related to the return and  $\alpha$  is the threshold restricting the values of this function. Consequently, side information can be used in the formulation of such constraints.

On the other hand, Safe Exploration modifies the exploration process subject to external knowledge, which in our case translates to incorporating side information into the exploration process. While intuitively, this overlaps with the usage of side information for directed exploration, a distinguishing feature of this work is the final goal of this directed exploration to be safety, which might potentially come at the cost of sample efficiency and/or generalization.

## 4. Structure as Side Information

Structure can be considered a particular kind of side information available to a learning agent. To build an intuition about what we mean by this, consider the task of managing a

large factory with many production cells <sup>1</sup>. If a cell positioned early in the production line generates faulty parts, the whole factory may be affected. However, the quality of the parts a cell generates depends directly only on the state of this cell and the quality of the parts it receives from neighboring cells. Additionally, the cost of running the factory depends, among other things, on the sum of the costs of maintaining each local cell. Finally, while a cell responsible for anodization may receive parts directly from any other cell in the factory, a work order for a cylindrical part may restrict this dependency to cells with a lathe. In the context of producing cylindrical parts, the quality of the anodized parts depends directly only on the state of cells with a lathe. Thus, by incorporating information about the additive nature of production, costs, and the context of the part that needs to be produced, the learning pipeline can be imbued with better objectives such as improved sample efficiency or robustness of a learned policy to changing factory conditions.

The vanilla MDP framework does not require incorporating such additive information into the learning pipeline. Thus, biasing the pipeline with this amounts to incorporating side information. However, this information particularly helps decompose the complicated learning problem into additive sub-parts that can be learned independently and, potentially, more efficiently. Thus, structure is a particular kind of side information that provides the learning pipeline with knowledge about decomposability in the learning problem.

In this section, we discuss the relationship between structure and decomposability. In Section 4.1, we explain the impact of structural side information by explaining how it decomposes complex systems and categorizes such decompositions into four archetypes. In Section 4.2 - Section 4.5, we discuss these archetypes further to connect them with existing literature.

## 4.1 Decomposability and Structural Archetypes

Decomposability is the property of a system that allows breaking it down into smaller components or subsystems that can be analyzed, understood, and potentially learned more efficiently than the larger system, independently (Hofer, 2017). In a decomposable system, the short-term behavior of each subsystem is approximately independent of the short-term behavior of the other subsystems. In the long run, the behavior of any one subsystem depends on the behavior of the other subsystems only in an aggregated way.

Concerning the RL pipeline in Figure 2, we can see decomposability along two axes: (i) Problem Decomposition i.e., the environment parameterization, states, actions, transitions, and rewards; (ii) Solution Decomposition i.e., the learned policies, value functions, models, and training procedures. The spectrum of decomposability (Hofer, 2017) provides an intuitive way to understand where a system lies in this regard. On one end of the spectrum, problems are non-decomposable, while on the other end, problems can be decomposed into weakly interacting sub-problems. Similarly, solutions on the former are monolithic, while those on the latter are modular. We capture this problem-solution interplay by marking four different archetypes of decomposability, as shown in Figure 3.

<sup>1.</sup> example taken from Guestrin et al. (2003b)

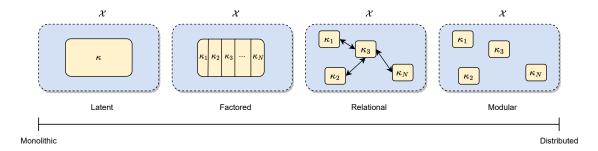


Figure 3: Spectrum of Decomposability and Structural Archetypes. On the left end of the spectrum exist monolithic structural decompositions where knowledge about a *latent* subspace of  $\mathcal{X}$  can be learned and incorporated as an inductive bias. Moving towards the right, we can learn multiple independent subspaces, albeit in a monolithic solution. These are *factored* decompositions. Further ahead, we see the emergence of interactionally complex decompositions, where knowledge about factorization and how they relate to each other can be incorporated into the learning process. We call these *relational decompositions*. Finally, we see fully distributed subsystems that can be incorporated and learned using individual policies. We call these *modular decompositions*.

## 4.2 Latent Decomposition

Latent decompositions are monolithic and can be useful in complex environments where the underlying structure is either unclear or non-stationary. Under this view, a pipeline component  $\mathcal{X}$  can be approximated by a latent representation  $\kappa$ , which can then be integrated into the learning process. The quantities in the update that depend on  $\mathcal{X}$  can now be re-conditioned on  $\kappa$ , which helps in improving performance by reducing the dimensionality of  $\mathcal{X}$ .

Latent States and Actions. Latent state spaces have been classically explored through the Latent MDP literature (Kwon et al., 2021), where the aim is to discover a latent representation of the state space that is sufficient to learn an optimal policy. Latent states are used for tackling rich observation spaces, where Block MDPs (Du et al., 2019) and Contextual MDPs (Hallak et al., 2015) have shown success in generalization problems. Latent actions have been similarly explored in settings with stochastic action sets (Boutilier et al., 2018).

Given an encoder  $\phi : \mathcal{S} \times \mathcal{A} \to \kappa$  and a decoder  $\beta : \kappa \to \mathcal{S}$ , the latent state-action formulation allows decomposing transition dynamics into a low-rank approximation,

$$P(s' \mid s, a) = \langle \phi(\kappa \mid s, a) \beta(s' \mid \kappa) \rangle.$$

**Latent Transition and Rewards.** While latent states allow decomposing transition matrices, another way to approach the problem directly is to decompose transition matrices into low-rank approximations:

$$P(s' \mid s, a) = \phi(s' \mid s, a)\beta(s' \mid s, a).$$

Linear MDPs (Papini et al., 2021) and corresponding applications in Model-based RL (Woo et al., 2022; van Rossum et al., 2021) have studied this form of direct decomposition.

A similar decomposition can be applied to rewards as well. Wang et al. (2020) have primarily explored this in noisy reward settings where the reward signal is assumed to be generated from a latent function that can be learned as an auxiliary learning objective.

## 4.3 Factored Decomposition

The factored decomposition moves slightly away from the monolithic nature by decomposing  $\mathcal{X}$  into (latent) factors  $\kappa_1, \ldots, \kappa_n$ . Thus, the spaces become inner products of the individual factor spaces. A crucial aspect of factorization is that the factors can potentially impose conditional independence in their effects on the learning dynamics.

Factored States and Actions. Factored state and action spaces have been explored in the Factored MDPs (Kearns & Koller, 1999; Boutilier et al., 2000; Guestrin et al., 2003b). Methods in this setting traditionally capture next state distribution using mechanisms such as Dynamic Bayesian Networks (Mihajlovic & Petkovic, 2001).

Factorization in the action space has also been used for tackling high-dimensional actions (Mahajan et al., 2021). These methods either impose a factorized structure on subsets of a high-dimensional action set (Kim & Dean, 2002) or impose this structure through the Q-values that lead to the final action (Tang et al., 2022a). Crucially, these methods can potentially exploit some form of independence resulting from such factorization, either in the state representations or transitions.

Factored Transitions and Rewards. Combined with factored states or modeled independently, factored rewards have been used to model perturbed rewards and multi-objective settings (Mambelli et al., 2022). While Factored MDPs do not naturally lead to factored policies, combining state and reward factorization can lead to factorization of Q-values (Koller & Parr, 1999; Sodhani et al., 2022a).

#### 4.4 Relational Decomposition

Relational decompositions add a further notion of separability where in addition to the factored subsets, capturing immutable relations between them becomes important as well. Usually, these relations exist between entities in a scene and are used to formulate learning methods based on inductive logic (Dzeroski et al., 2001). Traditionally, such relations were limited to first-order logic, but the relational structure has also been captured through graphs.

The relational assumption posits that a space of predicates  $\beta$  can ground these entities, and it can be modeled as a set of rules (such as inductive logic) that define how  $z_i, z_j \in Z$  interact with each other. An extension of this is by capturing  $\beta$  as a graph  $G = \langle V, E \rangle$  where the vertices are  $z_i \in Z$  and the edges represent the relationship between them.

Using such a representation allows us to talk about generalization over the entities  $\kappa_i, \kappa_j$ , and forms of  $\beta$ . This helps us circumvent the dimensionality of enumerative spaces.

Relational States and Actions Classically, relational representations have been used to model state spaces in Relational MDPs (Dzeroski et al., 2001) and Object-Oriented

MDPs (Guestrin et al., 2003a; Diuk et al., 2008). They represent factored state spaces using first-order representations consisting of objects, predicates, and functions on them to describe a set of ground MDPs. Such representations can capture interactionally complex structures between entities much more efficiently. Additionally, permutations of the interactions between the entities can help define new MDPs that differ in their dynamics, thus, contributing towards work in generalization.

States can also be more generally represented as graphs (Janisch et al., 2020; Sharma et al., 2022), or by using symbolic inductive biases (Garnelo et al., 2016) fed to a learning module in addition to the original state.

Action relations help tackle instances where the agent has multiple possible actions available, and the set of actions is significantly large. These methods capture relations using either attention mechanisms (Jain et al., 2021b; Biza et al., 2022b) or graphs (Wang et al., 2019), thus offering scalability to high-dimensional action spaces. Additionally, relations between states and actions have helped define notions such as intents and affordances (Abel et al., 2015; Khetarpal et al., 2020).

Relational Value Functions and Policies Traditional work in Relational MDPs has also explored ways to represent and construct first-order representations of value functions and/or policies to generalize to new instances. These include Regression Trees (Mausam & Weld, 2003), Decision Lists (Fern et al., 2006), Algebraic Decision Diagrams (Joshi & Khardon, 2011), and Linear Basis Functions (Guestrin et al., 2003a; Sanner & Boutilier, 2012). Recent approaches have started looking into DNN representations (Zambaldi et al., 2019; Garg et al., 2020), with extensions into modeling problem aspects such as morphology in Robotic tasks (Wang et al., 2018) in a relational manner, or using Graph-Laplacian (Mahadevan & Maggioni, 2007) representations for intrinsic rewards (Klissarov & Machado, 2023).

Relational Tasks A parallel line of work looks at capturing relations in a multi-task setting, where task perturbations are either in the form of goals and corresponding rewards (Sohn et al., 2018; Illanes et al., 2020; Kumar et al., 2022). Most work aims at integrating these relationships into the optimization procedure and/or additionally capturing them as models. We delve deeper into specifics in later sections.

## 4.5 Modular Decomposition

Modular decompositions exist at the other end of the spectrum of decomposability, where individual value functions and/or policies can be learned for each decomposed entity X. Specifically, a task can be broken down into individual subsystems  $\kappa_1, \ldots, \kappa_N$  for which models, value functions, and policies can be subsequently learned. Such modularity can exist along the following axes: (i) Spatial Modularity allows learning quantities specific to parts of the state space, thus, effectively reducing the dimensionality of the states; (ii) Temporal Modularity allows breaking down tasks into sequences over a learning horizon and, thus, learning modular quantities in a sequence; (iii) Functional Modularity allows decomposing the policy architecture into functionally modular parts, even if the problem is spatially and temporally monolithic.

A potential consequence of such breakdown is the emergence of a hierarchy, and when learning problems exploit this hierarchical relationship, these problems come under the purview of Hierarchical RL (HRL) (Pateria et al., 2022). The learned policies can also exhibit a hierarchy, where each policy can choose the lower-level policies to execute the subtasks. Each level can be treated as a planning problem (Yang et al., 2018) or a learning problem (Sohn et al., 2018), thus, allowing solutions to combine planning and learning through the hierarchy. Hierarchy, however, is not a necessity for modularity.

Modularity in States and Goals Modular decomposition of state spaces is primarily studied at high-level planning and state-abstractions for HRL methods (Kokel et al., 2021). Additionally, the literature on skills has looked into the direction of training policies for individual parts of the state-space (Goyal et al., 2020). Similarly, partial models only make predictions or specific parts of the observation-action spaces in Model-Based settings (Talvitie & Singh, 2008; Khetarpal et al., 2021). Goals have been specifically considered in methods that either use goals as an interface between levels of hierarchy (Kulkarni et al., 2016; Nachum et al., 2018; Gehring et al., 2021), or as outputs of task specification methods (Jiang et al., 2019; Illanes et al., 2020).

Modularity in Actions Modularity in action spaces refers to conditioning policies on learned action abstractions. The classic example of such methods belongs to the realm of the options framework where policies are associated with temporal abstractions over actions (Sutton et al., 1999b). In HRL methods, learning and planning of the higher levels are based on the lower-level policies and termination conditions of their execution.

Compositional Policies Continual settings utilize policies compositionally by treating already learned policies as primitives. Such methods either feed these primitives to the discrete optimization problems for selection mechanisms or to continuous optimization settings involving ensembling (Song et al., 2023) and distillation (Rusu et al., 2016). Modularity in such settings manifests itself by construction and is a central factor in building solutions. Even though the final policy in such paradigms, obtained through ensembling, selection, and/or distillation, can be monolithic, the method of obtaining such policies is a purely distributed regime.

## 5. Patterns of Incorporating Structure

Having defined different forms of decomposability and the different objectives that side information can be used to accomplish, we now connect the two by understanding the ways of incorporating structure into a learning process. We assume that some form of structure exists in the problem and/or the solution space, which can be incorporated into the learning pipeline as an inductive bias. To understand how decomposability can be incorporated into the RL pipeline, we survey the literature with a very specific question in mind: Do existing methods use structure in a repeatable manner? The answer to this question, inspired by the categorization of Jonschkowski et al. (2015) for the supervised learning case, brings us to patterns of incorporating structure.

A pattern is a principled change in the RL pipeline  $\Omega$  that allows the pipeline to achieve one, or a combination of, the additional objectives: Sample Efficiency, Generalization, Safety, and Interpretability. We categorize the literature into seven patterns, an overview of which has been shown in Figure 4. Our proposed patterns come from our literature survey and are meant to provide an initial direction for such categorization. We do not consider this list

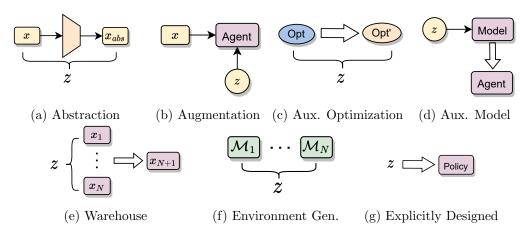


Figure 4: **Patterns of incorporating structural information.** We categorize the methods of incorporating structure as inductive biases into the learning pipeline into patterns that can be applied for different kinds of usages.

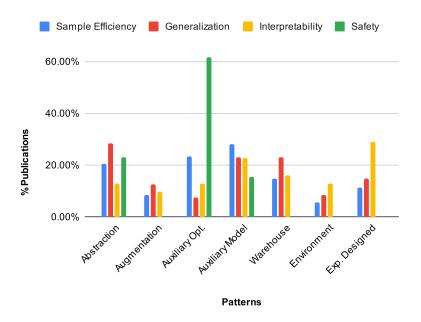


Figure 5: **Proclivities.** A meta-analysis of the proclivities of each pattern to the additional objectives. On the x-axis are the patterns discussed in this text, while on the y-axis are the percentage of publications for each additional objective that address it using a particular pattern.

exhaustive but more as a starting point to build further upon. We present an overview of our meta-analysis on the patterns used for which of the four use cases in Figure 5.

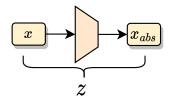
In the following subsections, we delve deeper into each pattern, explaining different lines of literature that apply each pattern for different use cases. To further provide intuition about this categorization, we will consider the running example of a taxi service, where the

task of the RL agent (the taxi) is to pick up passengers from various locations and drop them at their desired destinations within a city grid. The agent receives a positive reward when a passenger is successfully dropped off at their destination and incurs a small penalty for each time step to encourage efficiency.

For each of the following sections, we present a table of the surveyed methods that categorizes the work in the following manner: (i) The structured space, information about which is incorporated as side information; (ii) The type of decomposition exhibited for that structured space. We specifically categorize works that use structured task distributions through goals and/or rewards; (iii) The additional objectives for which the decomposition is utilized. In addition to demonstrating our categorization, our rationale behind the table format is to highlight the areas where further research might be lucrative. These are the spots in the tables where we could not yet find literature, and/or we believe additional work can be important.

#### 5.1 Abstraction Pattern

Abstraction pattern utilizes structural information to create abstract entities in the RL pipeline. For any entity, X, an abstraction utilizes the structural information to create  $X_{abs}$ , which takes over the role of X in the learning procedure. In the taxi example, the state space can be abstracted to the current grid cell of the taxi, the destination grid cell of the current passenger, and whether the



taxi is currently carrying a passenger. This significantly simplifies the state space compared to representing the full details of the city grid. The action space could also be abstracted to moving in the four cardinal directions, plus picking up and dropping off a passenger. Finding appropriate abstractions can be a challenging task in itself. Too much abstraction can lead to loss of critical information, while too little might not significantly reduce complexity (Jiang, 2018). Consequently, learning-based methods that jointly learn abstractions factor this granularity into the learning process.

Abstractions have been thoroughly explored in the literature, with early work addressing a formal theory on state abstractions (Li et al., 2006). Recent works have primarily used abstractions for tackling generalization. Thus, we see in Figure 5 that generalization is the most explored use case for abstractions. However, the aforementioned advantages of abstraction usually interleave these approaches with sample efficiency gains and safety as well. Given the widespread use of abstractions in the literature, we explore how different forms of abstractions impact each use case in the following paragraphs.

Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
Goals	Latent	Gallouedec and Dellandrea (2023)	Hansen-Estruch et al. (2022), Gallouedec and Dellandrea (2023)		
	Relational			Prakash et al. (2022)	

	Modular	Icarte et al. (2022)	Icarte et al. (2022)	Prakash et al. (2022), Icarte et al. (2022)	
States	Latent	Zhang et al. (2022), Ghorbani et al. (2020), Allen et al. (2021), Zhang et al. (2021), Gelada et al. (2019), Lee et al. (2020a), Azizzadenesheli et al. (2016), Misra et al. (2020)	Lee et al. (2020a), Zhang et al. (2021a), Gelada et al. (2019), Zhang et al. (2020), Misra et al. (2020)	Gillen and Byl (2021)	Yang et al. (2022), Gillen and Byl (2021)
	Factored	Sodhani et al. (2022a)	Higgins et al. (2017), Sodhani et al. (2021), Perez et al. (2020), Sodhani et al. (2022a)	Sodhani et al. (2021), Bewley and Lecune (2022), Kooi et al. (2022)	
	Relational	Martinez et al. (2017), Garnelo et al. (2016), Kipf et al. (2020), Kokel et al. (2021), Klissarov and Machado (2023)	Janisch et al. (2020), Kokel et al. (2021), Bapst et al. (2019), Adjodah et al. (2018), Garnelo et al. (2016), Kipf et al. (2020), Karia and Srivastava (2022)	Adjodah et al. (2018), Garnelo et al. (2016)	
	Modular	Kokel et al. (2021), Icarte et al. (2022), Furelos-Blanco et al. (2021)	Kokel et al. (2021), Steccanella et al. (2021), Icarte et al. (2022), Furelos- Blanco et al. (2021)	Icarte et al. (2022), Furelos-Blanco et al. (2021)	
Actions	Latent	Zhao et al. (2019), Chandak et al. (2019)			
	Factored Relational	Christodoulou et al.	Perez et al. (2020)  Bapst et al. (2019)	Bewley and Lecune (2022)	
	Tterational	(2019)	Dapst et al. (2019)		
	Modular	Furelos-Blanco et al. (2021)	Steccanella et al. (2021), Furelos-Blanco et al. (2021)	Furelos-Blanco et al. (2021)	
Rewards	Latent		Zhang et al. (2021a), Barreto et al. (2017), Barreto et al. (2018), Borsa et al. (2016)		
	Factored	Sodhani et al. (2022a)	Perez et al. (2020), Sodhani et al. (2022a), Sodhani et al. (2021),	Sodhani et al. (2021)	Wang et al. (2020)
Dynamics	Latent	Zhang et al. (2020)	Zhang et al. (2020), Borsa et al. (2019), Perez et al. (2020), Zhang et al. (2021a)		
	Factored	Fu et al. (2021)	Fu et al. (2021)		
	Modular	Sun et al. (2021)	Sun et al. (2021)		

**Generalization.** State abstractions are a standard choice for improving generalization performance by capturing shared dynamics across MDPs into abstract state spaces using

methods such as Invariant Causal Prediction (Peters et al., 2016; Zhang et al., 2020), similarity metrics (Zhang et al., 2021a; Hansen-Estruch et al., 2022; Castro et al., 2021; Lan et al., 2021; Agarwal et al., 2021; Lan & Agarwal, 2023; Castro et al., 2023), Free Energy Minimization (Ghorbani et al., 2020), and disentanglement (Higgins et al., 2017; Burgess et al., 2019).

Value functions can serve as temporal abstractions for shared dynamics in Multi-task Settings. Successor Features (SF) (Dayan, 1993; Barreto et al., 2017) exploit latent reward and dynamic decompositions by using value functions as an abstraction. Subsequent works have combined them with Generalized Policy Iteration (Barreto et al., 2018) and Universal Value Function Approximators (Schaul et al., 2015; Borsa et al., 2019). Factorization in value functions, other the other hand, can help improve sample efficiency and generalization both (Sodhani et al., 2021, 2022a).

Relational abstractions contribute to generalization by incorporating symbolic spaces into the RL pipeline. These can help incorporate planning approaches in hierarchical frameworks (Janisch et al., 2020; Kokel et al., 2021). Additionally, relational abstractions can help abstract away general aspects of a collection of MDPs, thus allowing methods to learn generalizable Q-values over abstract states and actions that can be transferred to new tasks (Karia & Srivastava, 2022) or develop methods specifically for graph-structured spaces (Bapst et al., 2019; Kipf et al., 2020).

Abstractions can additionally enable generalization in hierarchical settings by compressing state spaces (Steccanella et al., 2021), abstract automata (Furelos-Blanco et al., 2021; Icarte et al., 2022), templates of dynamics across tasks (Sun et al., 2021), or even be combined with options to preserve optimal values (Abel et al., 2020).

Sample Efficiency. Latent variable models improve sample efficiency across the RL pipeline. Latent state abstractions can improve sample efficiency in Model-based RL (Gelada et al., 2019) and also help improve the tractability of policy learning over options in HRL (Steccanella et al., 2021). In model-free tasks, these can also be learned as inverse models for visual features (Allen et al., 2021) or control in a latent space (Lee et al., 2020a). Latent transition models demonstrate efficiency gains by capturing task-relevant information in noisy settings (Fu et al., 2021), by preserving bisimulation distances between original states (Zhang et al., 2021), or by utilizing factorized abstractions (Perez et al., 2020). Learned latent abstractions (Gallouedec & Dellandrea, 2023) can also contribute to the exploration mechanism in the Go-Explore regime (Ecoffet et al., 2021).

Latent action models can expedite convergence of policy gradient methods such as REINFORCE (Williams, 1992b)) by shortening the learning horizon in stochastic scenarios like dialog generation Zhao et al. (2019). Action embeddings, on the other hand, can help reduce the dimensionality of large action spaces Chandak et al. (2019)

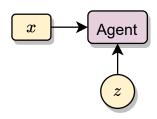
Safety and Interpretability. Relational abstractions are a very good choice for interpretability since they capture interactionally complex decompositions. The combination of object-centric representations and learned abstractions can help add transparency (Adjodah et al., 2018) while symbolic interjections, such as tracking the relational distance between objects, can help improve performance (Garnelo et al., 2016).

State and rewards abstractions can help with safety. Latent states can help to learn safe causal inference models by embedding confounders (Yang et al., 2022) On the other hand,

meshes (Talele & Byl, 2019; Gillen & Byl, 2021) help benchmark metrics such as robustness in a learned policy.

## 5.2 Augmentation Pattern

The augmentation pattern treats X and z as separate input entities for the action-selection mechanism. The combination can range from the simple concatenation of structural information to the state or actions to more involved methods of conditioning policy or value functions on additional information. Crucially, the structural information neither directly influences the optimization procedure nor changes the nature of X. It simply aug-



ments the already existing entities. In this view, abstractions that are learned in an auxiliary manner and concatenated to states, actions, or models can also be considered augmentations since the original entity remains unchanged.

For the taxi example, one way to apply the augmentation pattern would be by conditioning the policy on additional information, such as the time of day or day of the week. This information could be useful because traffic conditions and passenger demands can vary depending on these factors. However, augmentations can increase the complexity of the policy, and care needs to be taken to ensure that the policy does not overfit the additional information. Due to this, this pattern is generally not explored to its fullest extent. While we see usages of augmentations equitably for most use cases in Figure 5, the number of papers utilizing this pattern still falls short compared to more established techniques, such as abstraction. In the next paragraphs, we delineate three kinds of augmentations in the surveyed work.

Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
	Latent		Andreas et al.		
Goals			(2018), Schaul et al.		
Goals			(2015)		
	Factored	Islam et al. (2022)	Jiang et al. (2019)		
	Relational	Andreas et al.	Andreas et al.		
		(2018)	(2018), Jiang et al.		
			(2019)		
	Modular	Gehring et al.	Jiang et al. (2019),	Beyret et al. (2019)	
		(2021), Beyret et al.	Gehring et al.		
		(2019)	(2021)		
	Latent	Islam et al. (2022),	Andreas et al.		
States		Andreas et al.	(2018), Sodhani		
States		(2018), Gupta et al.	et al. (2022b),		
		(2018)	Gupta et al. (2018)		
	Factored	Islam et al. (2022)			
	Relational	Andreas et al.	Andreas et al.		
		(2018)	(2018)		
	Modular				
	Latent	Tennenholtz and	Jain et al. (2021b),		
Actions		Mannor (2019)	Jain et al. (2020)		
	Relational		Jain et al. (2021b)		
	Modular	Devin et al. (2019)	Pathak et al.		
			(2019), Devin et al.		
			(2019)		

Rewards	Factored	Huang et al. (2020)	Huang et al. (2020)		
Dynamics	Latent	Wang and van Hoof (2022)	Sodhani et al. (2022b), Guo et al. (2022), Wang and van Hoof (2022)		
	Factored		Goyal et al. (2021)		
Policies	Modular	Raza and Lin (2019), Haarnoja et al. (2018a), Marzi et al. (2023)	Haarnoja et al. (2018a)	Verma et al. (2018)	

Context-based Augmentations. Contextual representations of dynamics (Sodhani et al., 2022b; Guo et al., 2022) and goal-related information (Nachum et al., 2018; Islam et al., 2022) can help with generalization and sample efficiency by exposing the agent to the necessary information for optimality. Goal augmentations additionally allow interpretable mechanisms for specifying goals (Beyret et al., 2019). On the other hand, augmentation of meta-learned latent spaces to the normal state can promote temporally coherent exploration across tasks (Gupta et al., 2018). Action histories (Tennenholtz & Mannor, 2019) can directly help with sample efficiency, and action relations (Jain et al., 2020, 2021b) contribute to generalization over large action sets.

Language Augmentations. Language can explicitly capture relational metadata in the world. Latent language interpretation models (Andreas et al., 2018) can utilize the compositionality of language to achieve better exploration and generalization to different relational settings, as represented by their language descriptions. On the other hand, goal descriptions (Jiang et al., 2019) can help hierarchical settings by exploiting semantic relationships between different subtasks and producing better goals for lower-level policies. Augmentations can additionally help make existing methods more interpretable through methods such as Verma et al. (2018) by guiding search over approximate policies written in human-readable formats.

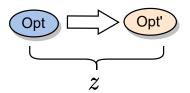
Control Augmentations. Augmentations can additionally help with primitive control, such as multi-level control in hierarchical settings. Augmenting internal latent variables conditioned on primitive skills (Haarnoja et al., 2018a; Gehring et al., 2021; Devin et al., 2019) can help tackle sample efficiency in hierarchical settings. Augmentations can also help morphological control (Huang et al., 2020) through methods such as Pathak et al. (2019) that model the different limbs as individual agents that need to learn to join together into a morphology to solve a task.

## 5.3 Auxiliary Optimization Pattern

This pattern uses structural side information to modify the optimization procedure. This includes methods involving contrastive losses, reward shaping, concurrent optimization, masking strategies, regularization, baselining, etc. However, given that the changes in the optimization can go hand-in-hand with modifications of other components, this pattern shares methods with many other patterns. For example, contrastive losses can be used to

learn state abstractions. Similarly, a learned model can be utilized for reward shaping as well. Thus, methods that fall into this category simultaneously utilize both patterns.

In the case of the taxi, reward shaping could help the policy to be reused for slight perturbances in the city grid, where the shaped reward encourages the taxi to stay near areas where passengers are frequently found when it does not have a passenger. It is crucial to ensure that the modified optimization process remains aligned with the original objective, i.e., there needs to exist some form of regularization that controls how the modification of



the optimization procedure respects the original objective. For reward shaping techniques, this amounts to the invariance of the optimal policy under the shaped reward (Ng et al., 1999). For auxiliary objectives, this manifests in some form of entropy (Fox et al., 2016) or divergence regularization (Eysenbach et al., 2019). Constraints ensure this through recursion (Lee et al., 2022), while baselines control the variance of updates (Wu et al., 2018). The strongest use of constraints is in the safety literature, where constraints either help control the updates using some safety criterion or constrain the exploration. Consequently, in Figure 5, we see that the auxiliary optimization pattern peaks in its proclivity towards addressing safety. In the following paragraphs, we cover methods that optimize individual aspects of the optimization procedure, namely, rewards, learning objectives, constraints, and parallel optimization.

Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
	Latent		Wang et al. (2023)		
Goals	Relational		Kumar et al.		
			(2022)		
	Factored			Alabdulkarim and	
				Riedl (2022)	
	Modular	Nachum et al.			
		(2018), Illanes			
		et al. (2020), Li			
		et al. (2021),			
		Gehring et al.			
		(2021)			
	Latent	Mahajan and Tu-		Harutyunyan et al.	Zhang et al. (2020),
States		labandhula (2017),		(2019)	Yu et al. (2022)
States		Li et al. (2021), Az-			
		izzadenesheli et al.			
		(2016), Ok et al.			
		(2018), Amin et al.			
		(2021a), Nachum			
		et al. (2018), Ghor-			
		bani et al. (2020),			
		Yang et al. (2020b),			
		Henaff et al. (2022)			
	Factored	Tavakol and			Lee et al. (2022)
		Brefeld (2014),			
		Trimponias and			
		Dietterich (2023),			
		Ross and Pineau			
		(2008), lyu et al.			
		(2023)			
	Relational	Li et al. (2021)			

	Modular	Nachum et al. (2018), Khetarpal et al. (2020)		Lyu et al. (2019)	
Actions	Latent	Ok et al. (2018), Amin et al. (2021a), Yang et al. (2020b), lyu et al. (2023)	Gupta et al. (2017)	Zhang and Yu (2021)	Zhang et al. (2019a), Zhang et al. (2019b), Zhang and Yu (2021)
	Factored	Balaji et al. (2020), Wu et al. (2018), Tang et al. (2022a), Metz et al. (2017), Spooner et al. (2021), Tang et al. (2022b), Khamassi et al. (2017), Tavakol and Brefeld (2014)			
	Modular	Metz et al. (2017), Klissarov and Machado (2023)		Lyu et al. (2019)	Jain et al. (2021a)
Rewards	Factored	Trimponias and Dietterich (2023), Saxe et al. (2017), Huang et al. (2020)	Belogolovsky et al. (2021), Saxe et al. (2017), Buchholz and Scheftelowitsch (2019), Huang et al. (2020)		Prakash et al. (2020), Baheri (2020)
Dynamics	Latent Factored	Mu et al. (2022a), Henaff et al. (2022) Liao et al. (2021)	Lee and Chung (2021)  Belogolovsky et al. (2021), Buchholz		
	Relational	Mu et al. (2022a),	and Scheftelow- itsch (2019)		
		Illanes et al. (2020)			
Policy Space	Latent	Hausman et al. (2018)	Hausman et al. (2018), Gupta et al. (2017)		

Reward Modification. Reward shaping is a common way to incorporate additional information into the optimization procedure. Methods can gain sample efficiency by exploiting modular and relational decompositions through task descriptions (Illanes et al., 2020), or goal information from a higher level policy with off-policy modification to the lower level transitions (Nachum et al., 2018). Histories of rewards (Mahajan & Tulabandhula, 2017) can help learn symmetric relationships between states and, thus, improve the selection procedure for states in a mini-batch for optimization. Factorization of states and rewards into endogenous and exogenous factors (Trimponias & Dietterich, 2023), on the other hand, helps with safety and sample efficiency through reward corrections.

Extrinsic Rewards can also be used to guide the exploration process. Symbolic planning with relational representations can be used to interact with a primitive learning policy through extrinsic rewards in hierarchical settings, thus, adding interpretability while directly impacting the exploration through the extrinsic reward (Lyu et al., 2019). Alternatively, additional reward sources can help determine the quality of counterfactual trajectories, which can help explain why an agent took certain kinds of actions (Alabdulkarim & Riedl,

2022). Additionally, running averages can rewards be used to adaptively tune exploration parameters for heterogeneous action spaces (Khamassi et al., 2017)

On the other hand, intrinsic rewards can specifically help with exploration in sparse reward environments. Latent decompositions can help improve such methods by directly impacting the exploration. Language abstractions can serve as latent decompositions that can be separately used for exploration (Mu et al., 2022a). Alternatively, geometric structures can provide a way to compare state embeddings and provide episodic bonuses (Henaff et al., 2022).

Auxiliary Learning Objectives. Skill-based methods transfer skills between agents with different morphology by learning invariant subspaces and using those to create a transfer auxiliary objective (through a reward signal) (Gupta et al., 2017), or an entropy-based term for policy regularization (Hausman et al., 2018). In hierarchical settings, discovering appropriate sub-tasks (Solway et al., 2014) can be a highly sample-inefficient process. Li et al. (2021) tackle this by composing values of the sub-trajectories under the current policy, which they subsequently use for behavior cloning. Latent decompositions can help with robustness and safety when used for some form of policy regularization (Zhang et al., 2020). Auxiliary losses, which usually help with generalization, can also be a very good entry point for human-like inductive biases (Kumar et al., 2022). Metrics inspired by the geometry of latent decompositions can help learn optimal values in multi-task settings (Wang et al., 2023).

Constraints and Baselines. Constrained optimization is commonplace in Safe RL, and incorporating structure can help improve the sample efficiency of such methods while making them more interpretable. Factorization of states into safe and unsafe states can help develop persistent safety conditions (Yu et al., 2022), or language abstractions (Prakash et al., 2020). Recursive constraints (Lee et al., 2022) can help explicitly condition the optimization on a latent subset of safe actions using factored states. Restricting the exploration of options to non-risky states can help incorporate safety in hierarchical settings as well (Jain et al., 2021a). Factorized actions can also help improve the sample efficiency of policy gradient methods through baselining (Wu et al., 2018; Spooner et al., 2021), offline methods through direct value conditioning (Tang et al., 2022b), and value-based planning through matrix estimation (Yang et al., 2020b)

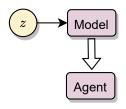
Methods can also directly incorporate expert domain knowledge directly in the action selection mechanism for safety and interpretability (Zhang & Yu, 2021), or for directed exploration to improve sample efficiency (Amin et al., 2021a). Hierarchical settings can benefit from latent state decompositions incorporated via modification of the termination condition (Harutyunyan et al., 2019). Additionally, state-action equivalences can help scale Q-learning to large spaces through factorization (lyu et al., 2023).

Concurrent Optimization. Parallelizing optimization using structural decompositions can specifically help with sample efficiency. Factored MDPs are a very good way to model factors that influence the content presented to users and can be used for ensembling methods in a parallel regime (Tavakol & Brefeld, 2014). Similarly, factored rewards in hierarchical settings can help decompose Multi-task problems into a linear combination of individual task MDPs (Saxe et al., 2017). Alternatively, discretizing continuous sub-actions in multi-dimensional action spaces can help extend the MDP for each sub-action to an undiscounted

lower-level MDP, modifying the backup for the Q values using decompositions (Metz et al., 2017). Relational decompositions can additionally help with masking strategies for Factored Neural Networks (Balaji et al., 2020).

## 5.4 Auxiliary Model Pattern

This pattern represents using the structural information in a model. In using the term model, we specifically refer to methods that utilize a model of the world to generate experiences, either fully or partially. This notion allows us to capture a range of methods, from ones using fullscale world models to generate rewards and next-state transitions to ones that use these methods to generate full experience sequences. In our categorization, we specifically



look at how the structure is incorporated into such models to help generate some parts of learning experiences.

Our taxi agent could learn a latent model of city traffic based on past experiences. This model could be used to plan routes that avoid traffic and hence reach destinations faster. Alternatively, the agent could learn an ensembling technique to combine multiple models, each of which model-specific components of the traffic dynamics. With models, there is usually a trade-off between model complexity and accuracy, and it is essential to manage this carefully to avoid overfitting and maintain robustness. To this end, incorporating structure helps make the model-learning phase more efficient while allowing reuse for generalization. Hence, in Figure 5, we see that the auxiliary model pattern shows a strong proclivity to utilizing structure for sample efficiency. In the following paragraphs, we explicitly discuss models that utilize decompositions and models used for creating decompositions.

Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
	Factored		Ding et al. (2022)		
Goals	Relational		Sohn et al. (2018),		
			Sohn et al. (2020)		
	Modular	Icarte et al. (2022)	Icarte et al. (2022)	Icarte et al. (2022)	
	Latent	Gasse et al. (2021),	van der Pol et al.		Simao et al. (2021)
Chahaa		Wang et al. (2022),	(2020), Wang et al.		
States		Hafner et al. (2023),	(2022), Hafner et al.		
		van der Pol et al.	(2023), Hafner et al.		
		(2020), Ghorbani	(2020), Zhang et al.		
		et al. (2020), Tsi-	(2021a), Tsividis		
		vidis et al. (2021),	et al. (2021)		
		Yin et al. (2023)	, ,		
	Factored	Innes and Las-	Young et al. (2022),		
		carides (2020),	Ding et al. (2022)		
		Seitzer et al.	, ,		
		(2021), Andersen			
		and Konidaris			
		(2017), Ross and			
		Pineau (2008),			
		Singh et al. (2021),			
		Pitis et al. (2020)			

	Relational	Chen et al. (2020), Biza et al. (2022b), Biza et al. (2022a), Kipf et al. (2020), Tsividis et al. (2021), Singh et al. (2021), Pitis et al. (2020)	Biza et al. (2022b), Biza et al. (2022a), Veerapaneni et al. (2020), Kipf et al. (2020), Tsividis et al. (2021)	Xu and Fekri (2021)	
	Modular	Abdulhai et al. (2022), Andersen and Konidaris (2017), Icarte et al. (2022), Furelos-Blanco et al. (2021)	Icarte et al. (2022), Furelos-Blanco et al. (2021)	Icarte et al. (2022), Furelos-Blanco et al. (2021)	
Actions	Latent	van der Pol et al. (2020)	van der Pol et al. (2020)		
rectons	Factored	Spooner et al. (2021), Geißer et al. (2020), Innes and Lascarides (2020), Pitis et al. (2020)	Ding et al. (2022)		
	Relational	Biza et al. (2022b), Pitis et al. (2020)	Biza et al. (2022b)		
	Modular	Furelos-Blanco et al. (2021), Yang et al. (2018)	Furelos-Blanco et al. (2021)	Furelos-Blanco et al. (2021)	
Rewards	Latent	van der Pol et al. (2020)	Zhang et al. (2021a), van der Pol et al. (2020), Lee and Chung (2021), Sohn et al. (2018), Sohn et al. (2020)		
	Factored		Sohn et al. (2018)		Wang et al. (2020), Baheri (2020)
Dynamics	Latent	Woo et al. (2022), Fu et al. (2021), van der Pol et al. (2020), Wang and van Hoof (2022)	Zhang et al. (2021a), Woo et al. (2022), van der Pol et al. (2020), Fu et al. (2021), Guo et al. (2022), Wang and van Hoof (2022)	van Rossum et al. (2021)	
	Factored	Fu et al. (2021), Schiewer and Wiskott (2021)	Goyal et al. (2021), Fu et al. (2021)	Schiewer and Wiskott (2021), Kaiser et al. (2019)	
	Relational	Buesing et al. (2019)			
	Modular	Abdulhai et al. (2022), Wu et al. (2019), Wen et al. (2020)	Wu et al. (2019)		

Models with structured representations. Young et al. (2022) utilize factored decomposition for state space to demonstrate the benefits of model-based methods in combinatorially complex environments. Similarly, the dreamer models (Hafner et al., 2020, 2023) utilize latent representations of pixel-based environments.

Object-oriented representation for states can help bypass the need to learn latent factors using CNNs in MBRL (Biza et al., 2022a) or as random variables whose posterior can be

refined using NNs (Veerapaneni et al., 2020). Graph (Convolutional) Networks (Zhang et al., 2019c) can capture rich higher-order interaction data, such as crowd navigation Chen et al. (2020), or invariances (Kipf et al., 2020). Action equivalences can help learn latent models (Abstract MDPs) (van der Pol et al., 2020) for planning and value iteration.

Models for task-specific decompositions. Another way to utilize decompositions in models is to capture task-specific decompositions. Models that capture some form of relevance, such as observational and interventional data in Causal RL (Gasse et al., 2021), or task-relevant vs. irrelevant data (Fu et al., 2021) can help with generalization and sample efficiency gains. Latent representations help models capture control-relevant information (Wang et al., 2022) or subtask dependencies (Sohn et al., 2018).

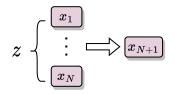
Models for safety usually incorporate some measure of cost to abstract safe states (Simao et al., 2021), or unawareness to factor states and actions (Innes & Lascarides, 2020). Alternatively, models can also directly guide exploration mechanisms through latent causal decompositions (Seitzer et al., 2021) and state subspaces (Ghorbani et al., 2020) to gain sample efficiency. Generative methods such as CycleGAN (Zhu et al., 2017) are also very good ways to use Latent models of different components of an MDP to generate counterfactual trajectories (Woo et al., 2022)

#### 5.5 Warehouse Pattern

This pattern uses structural information to create a database of entities that can be combined to achieve a specific objective. These can be learned policies and value functions or even models. Given the online nature of such methods, they are often targeted toward continual and life-long learning problems. The inherent modularity in such methods often leads them to focus on knowledge reuse as a central theme.

The taxi from our running example could maintain a database of value functions or policies for different parts of the city or at different times of the day. These could be reused as the taxi navigates through the city, making learning more efficient. While warehousing generally can improve efficiency, it has primarily been explored through the skills and options framework for targeting generalization. An important consideration in warehousing is managing the warehouse's size and diversity to avoid biasing the learning process too much toward past experiences.

So far, the warehousing pattern seems to be applied to sample efficiency and generalization. However, warehousing also overlaps with interpretability since the stored data can be easily used to analyze the agent's behavior and understand the policy for novel scenarios. Consequently, these objectives are equitably distributed in Figure 5.



Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
	Factored		Mendez et al.		
Goals			(2022b), Devin		
			et al. (2017)		
	Relational			Prakash et al.	
				(2022)	

	Modular	Gehring et al. (2021)	Mendez et al. (2022b)	Prakash et al. (2022)	
States	Latent		Hu and Montana (2019), Bhatt et al. (2022)		
	Factored	Mankowitz et al. (2015), Yarats et al. (2021)	Mendez et al. (2022b), Goyal et al. (2020), Yarats et al. (2021)		
	Modular	Furelos-Blanco et al. (2021)	Mendez et al. (2022b), Goyal et al. (2020), Furelos-Blanco et al. (2021)	Furelos-Blanco et al. (2021)	
A -4:	Latent		Gupta et al. (2017)		
Actions	Modular	Li et al. (2018), Furelos-Blanco et al. (2021), Devin et al. (2019)	Furelos-Blanco et al. (2021), Devin et al. (2019), Nam et al. (2022), Peng et al. (2019), Bar- reto et al. (2019), Sharma et al. (2020), Xu et al. (2020)	Furelos-Blanco et al. (2021)	
Rewards	Factored		Haarnoja et al. (2018b), Mendez et al. (2022b), Gaya et al. (2022a), Gaya et al. (2022b)		
Dynamics	Latent		Bhatt et al. (2022)		
2 j namies	Factored	Shyam et al. (2019), Schiewer and Wiskott (2021)	Devin et al. (2017), Mendez et al. (2022b)	Schiewer and Wiskott (2021)	
	Modular	Wu et al. (2019)	Gaya et al. (2022a), Gaya et al. (2022b), Mendez et al. (2022b), Wu et al. (2019)		
Policies	Latent Modular	Wolf and Musolesi (2023), Florensa et al. (2017), Heess et al. (2016), Eysenbach et al. (2019), Raza and Lin (2019), Mankowitz et al. (2015), Mendez et al. (2020), Hausman et al. (2018)	Gupta et al. (2017)  Florensa et al. (2017), Heess et al. (2016), Mendez et al. (2020), Kaplanis et al. (2019), Hausman et al. (2018)	Verma et al. (2018)  Verma et al. (2018)	

**Policy Warehousing.** Policy subspaces (Gaya et al., 2022b) is a relatively new concept that utilizes shared latent parameters in policies to learn a subspace that can be subsequently combined linearly to create new policies. Extending these subspaces by warehousing additional policies naturally extends them to continual settings (Gaya et al., 2022a).

Using goals and rewards, task factorization endows warehousing policies and Q values in multi-task lifelong settings. The multi-task lifelong problem can also be treated as a relationship graph between existing tasks generated from latent space (Mendez et al.,

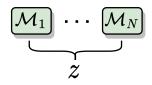
2022b). On the other hand, methods such as Devin et al. (2017) factor MDPs into agent-specific and task-specific degrees of variation, for which individual modules can be trained. Disentanglement using variational encoder-decoder models (Hu & Montana, 2019) can help control morphologically different agents by factorizing dynamics into shared and agent-specific factors. Additionally, methods such as Raza and Lin (2019) partition the agent's problem into interconnected sub-agents that learn local control policies.

Methods that utilize the skills framework effectively warehouse learned primitives, similar to how options warehouse associated policies in HRL. These can subsequently be used for maximizing mutual information in lower layers (Florensa et al., 2017), sketching together a policy (Heess et al., 2016), diversity-seeking priors in continual settings (Eysenbach et al., 2019), or for partitioned states spaces (Mankowitz et al., 2015). Similarly, Gupta et al. (2017) apply the warehouse pattern on a latent embedding space, learned using auxiliary optimization.

Decomposed Models. Decompositions that inherently exist in models lead to approaches that often ensemble multiple models that individually reflect different aspects of the problem. Ensemble methods such as Goyal et al. (2021) capture the dynamics in individual modules that sparsely interact and use attention mechanisms (Vaswani et al., 2017). Ensembling dynamics can also help with few-shot adaptation to unseen MDPs (Lee & Chung, 2021). Factored models can also be combined with relational decompositions to bind actions to object-centric representations Biza et al. (2022b). Latent representations in hierarchical settings (Abdulhai et al., 2022) can additionally improve the sample inefficiency of Deep Option Critic (Bacon et al., 2017).

#### 5.6 Environment Generation Pattern

This pattern uses structural information to create task, goal, or dynamics distributions from which MDPs can be sampled. This subsumes the idea of procedurally generated environments while additionally incorporating methods that use auxiliary models inducing structure in the environment generation process. The decomposition is reflected in the aspects of the environment generation that



are impacted by the generative process, such as dynamics, reward structure, state space, etc. Given the online nature of this pattern, methods in this pattern end up addressing curriculum learning in one way or another.

In the taxi example, a curriculum of tasks could be generated, starting with simple tasks (like navigating an empty grid) and gradually introducing complexity (like adding traffic and passengers with different destinations). Ensuring that the generated MDPs provide good coverage of the problem space is crucial to avoid overfitting to a specific subset of tasks. This necessitates additional diversity constraints that must be incorporated into the environment generation process. Structure, crucially, provides additional interpretability and controllability in the environment generation process, thus, making benchmarking easier than methods that use unsupervised techniques (Laskin et al., 2021).

Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
Goals	Relational	Illanes et al. (2020),	Kumar et al. (2022)	Gur et al. (2021)	
Goals		Gur et al. (2021)			
	Modular	Kulkarni et al.	Narvekar et al.		
		(2016), Illanes et al.	(2016), Mendez		
		(2020)	et al. (2022a)		
	Latent		Wang et al. $(2021)$ ,		
States			Bhatt et al. (2022)		
	Factored	Lu et al. (2018),	Mirsky et al. (2022)	Lu et al. (2018),	
		Mirsky et al. (2022)		Mirsky et al. (2022)	
	Relational	Lu et al. (2018),	Bauer et al. (2023)	Lu et al. (2018)	
		Bauer et al. (2023)			
	Latent		Wang et al. (2021),		
Rewards			Lee and Chung		
			(2021)		
	Factored	Chu and Wang	Mendez et al.		
	Ţ.,	(2023)	(2022a)		
	Latent		Kumar et al. (2021),		
Dynamics	-	61 1 777	Bhatt et al. (2022)	36.1 (2022)	
J	Factored	Chu and Wang	Mirsky et al.	Mirsky et al. (2022)	
		(2023), Mirsky et al.	(2022), Narvekar		
		(2022)	et al. (2016),		
			Mendez et al.		
	Relational	Illamas et al. (2020)	(2022a)	Warm at al (2021)	
	neiational	Illanes et al. (2020),	Wang et al. (2021),	Wang et al. (2021), Bauer et al. (2023)	
	Modular	Bauer et al. (2023)	Bauer et al. (2023)	\ /	
	Modular	Illanes et al. (2020),	Mirsky et al. (2022)	Mirsky et al. (2022)	
	[	Mirsky et al. (2022)			

The compositional nature of learning problems can be modeled using rule-based grammar. Kumar et al. (2021) particularly utilize this to impact the transition dynamics and generate environments. This allows them to train agents with an implicit compositional curriculum. This is further used by Kumar et al. (2022) in their auxiliary optimization procedure. Another way to capture task dependencies is through latent graphical models, which can be used to generate the state-space, reward functions, and transition dynamics (Wang et al., 2021; Bauer et al., 2023).

Latent dynamics models allow simulating task distributions, which can help with generalization (Lee & Chung, 2021). Clustering methods such as (Chu & Wang, 2023), on the other hand, explore task similarities by meta-learning a clustering method through an exploration policy. In a way, they recover a factored decomposition on the task space where individual clusters can be further used for policy adaptation.

## 5.7 Explicitly Designed

This pattern encompasses all methods where the inductive biases manifest in specific architectures or setups that reflect the decomposability of the problem that they aim to utilize. Naturally, this includes highly specific Neural architectures, but it also easily extends to other methods like sequential architectures to capture hierarchies, relations, etc. Crucially, the usage of structural information is limited to the specificity of the architecture and not any other part of the pipeline. In the case of the taxi, a neural architecture could be designed to process the city grid as an image and output a policy. Techniques like convolutional

layers could be used to capture the spatial structure of the city grid. Different network parts could be specialized for different subtasks, like identifying passenger locations and planning routes. However, this pattern involves a considerable amount of manual tuning and experimentation, and it's critical to ensure that these designs generalize well across different tasks. Designing specific neural architectures can provide better interpretability, enabling the ability to decompose different components and simulate them independently. Consequently, this pattern shows the highest proclivity to interpretability, with Generalization being a close second in Figure 5.

Space	Type	Efficiency	Generalization	Interpretabiltiy	Safety
Goals	Factored	Zhou et al. (2022)	Zhou et al. (2022)	Alabdulkarim and	
Goals				Riedl (2022)	
	Relational	Zhou et al. (2022)	Zhou et al. (2022)		
	Latent	Wang et al. (2016)	Yang et al. (2020a)		
States	Factored	Zhou et al. (2022)	Zhou et al. (2022)		
States	Relational	Zhou et al.	Zhou et al.	Zambaldi et al.	
		(2022),Mam-	(2022),Mam-	(2019), Payani and	
		belli et al.	belli et al.	Fekri (2020)	
		(2022),Shanahan	(2022),Shanahan		
		et al. (2020),Zam-	et al. (2020),Zam-		
		baldi et al. (2019)	baldi et al.		
		, ,	(2019),Lampinen		
			et al. (2022),		
			Sharma et al.		
			(2022)		
	Modular				
	Latent	Wang et al. (2016)			
Actions	Factored	Tavakoli et al.		Tavakoli et al.	
		(2018)		(2018)	
	Relational	Garg et al. (2020)		Garg et al. (2020)	
Rewards	Latent		Yang et al. (2020a)		
	Factored				Baheri (2020)
Dynamics	Latent	der Pol et al. (2020)	D'Eramo et al.		
Dynamics			(2020), Guo et al.		
			(2022)		
	Factored	Srouji et al.			
		(2018), Hong et al.			
		(2022)			
	Relational		Lampinen et al.		
			(2022)		
Policies	Relational	Oliva et al. (2022),	Wang et al. (2018)	Garg et al. (2020)	
		Garg et al. (2020)			
	Modular		Shu et al. (2018)	Shu et al.	
				(2018),Mu et al.	
				(2022b)	

Splitting Functionality. One way to bias the architecture is to split its functionality into different parts. Most of the works that achieve such disambiguation are either Factored or Relational. Structured Control Nets (Srouji et al., 2018) model linear and non-linear aspects of the dynamics individually and combine them additively to gain sample efficiency and generalization. Alternatively, Bi-linear Value Networks (Hong et al., 2022) architecturally decompose dynamics into state and goal-conditioned components to produce a goal-conditioned Q-function. Action Branching architectures (Tavakoli et al., 2018) used a shared representation that is then factored into separate action branches for individual

functionality. This approach bears similarity to capturing multi-task representations using bottlenecks (D'Eramo et al., 2020).

Relational and Modular biases manifest in hierarchical architectures. This also allows them to add more interpretability to the architecture. Two-step hybrid policies (Mu et al., 2022b), for example, demonstrate an explicit method to make policies more interpretable through splitting actions into pruners and selector modules. On the other hand, routing hierarchies explicitly capture modularity using sub-modules that a separate policy can use for routing them (Shu et al., 2018; Yang et al., 2020a).

Capturing Invariances in Architectures. Specialized architectures can also help capture invariance in the problem. Symbolic Networks (Garg et al., 2020; Sharma et al., 2022) train a set of shared parameters for Relational MDPs by first converting them to Graphs and then capturing node embeddings using Neural Networks. Homomorphic Networks (der Pol et al., 2020) capture symmetry into specialized MLP and CNN architectures. An alternate approach to incorporating symmetry is through basis functions (Wang et al., 2016).

Attention mechanisms can explicitly capture entity-factored scenarios (Janisch et al., 2020; Shanahan et al., 2020; Zhou et al., 2022). Relational and Graph Networks can capture additional relational inductive biases explicitly. Linear Relation Networks (Mambelli et al., 2022) provides an architecture that scales linearly with the number of objects. Graph networks have also been used to model an agent's morphology in embodied control explicitly (Wang et al., 2018; Oliva et al., 2022).

**Specialized Modules.** A class of methods combines the best of both worlds by capturing invariance in additional specialized modules. Such modules can capture relational structure in semantic meaning (Lampinen et al., 2022), relational encoders for auxiliary models (Guo et al., 2022), or specialized architectures for incorporating domain knowledge (Payani & Fekri, 2020).

## 6. Open Problems in Structured Reinforcement Learning

Having discussed our patterns-oriented framework for understanding how to incorporate structure into the RL pipeline, we now turn to connect our framework with existing sub-fields of RL. We examine existing paradigms in these sub-fields from two major perspectives: Scalability and Robustness. These dimensions serve as a canvas upon which we can position and understand different RL paradigms in sub-fields such as Offline RL, Unsupervised RL, Foundation Models in RL, Partial observability, Big Worlds, Automated RL, and Meta-RL.

Sparse data scenarios require more intelligent ways to use limited experiences, while abundant data scenarios might suffer from data quality since they might be generated from noisy and often unreliable sources.

**Scalability** measures how well methods scale with the increasing problem complexity in terms of the size of the state and action spaces, complex dynamics, noisy reward signals, and longer task horizons. On one hand, methods might specifically require low dimensional spaces and might not scale so well with increasing the size of these spaces, and on the other, some methods might be overkill for simple problems but better suited for large spaces.

Robustness measures the response of methods to changes in the environment. While the notion overlaps with generalization, robustness for our purposes more holistically looks at central properties of data distribution, such as initial state distributions and multi-modal evaluation returns. Under this notion, fundamentally different learning dynamics might be robust to different kinds of changes in the environment.

Structure of the Section. In the following subsections, we cover sub-fields of RL that lie at different points of the 2D space of Scalability and Robustness. We introduce the existing paradigms and the current challenges for each sub-field. We then present some examples in which our framework can bolster further research and practice in these fields. Finally, we collate this discussion into takeaways that can be combined into specific design patterns utilizing our framework.

#### 6.1 Offline RL

Offline Reinforcement Learning (also known as batch RL) (Prudencio et al., 2022) involves learning from a fixed dataset without further interaction with the environment. This approach can benefit when active exploration is costly, risky, or infeasible. Consequently, such methods are highly data-dependent due to their reliance on the collected dataset, and they do not generalize well due to the limitations of the pre-collected data. The three dominant paradigms in Offline RL – Behavior Cloning (Bain & Sammut, 1995), Q-Learning (Kumar et al., 2020), and Sequence Modelling (Chen et al., 2021) – uniformly degrade in performance as the state-space increases (Bhargava et al., 2023). Offline RL also comes with its own challenges, including overcoming distributional shifts and exploiting the available dataset effectively. Structural decomposition can play a crucial role in addressing these challenges in the following ways:

Improved Exploitation of Dataset. Task decomposition allows learning individual policies or value functions for different subtasks, which could potentially leverage the available data more effectively. For example, modular decomposition through warehousing separate policies for individual modules using the corresponding subset of the data might be more sample-efficient than learning a single policy for the entire task. Task decompositions, thus, open up new avenues for developing specialized algorithms that effectively learn from limited data about each subtask while balancing the effects of learning different subtasks. Practitioners can leverage such decompositions to maximize the utility of their available datasets by training models that effectively handle specific subtasks, potentially improving the overall system's performance with the same dataset.

Mitigating Distributional Shift. The structural information could potentially help mitigate the effect of distributional shifts. For instance, if some factors are less prone to distributional shifts in a factored decomposition, we could focus more on those factors during learning. This opens up venues for gaining theoretical insights into the complex interplay of structural decompositions, task distributions, and policy performance. On the other hand, practical methods for environments where distributional shifts are common could leverage structural decomposition to create more robust RL systems.

Auxiliary Tasks for Exploration. Structural decomposition can be used to define auxiliary tasks that facilitate learning from the dataset. For instance, in a relational

decomposition, we could define auxiliary tasks that involve predicting the relationships between different entities, which could help in learning a useful representation of the data. Using the proposed framework, researchers can explore how to define meaningful auxiliary tasks that help the agent learn a better representation of the environment. This could lead to new methods that efficiently exploit the available data by learning about these auxiliary tasks. Practitioners can design auxiliary tasks based on the specific decompositions of their problem. For example, if the task has a clear relational structure, auxiliary tasks that predict the relations between different entities can potentially improve the agent's understanding of the environment and its overall performance.

#### Offline RL Patterns

- Use a Factored or Relational decomposition to create abstractions that can help with distribution shift and auxiliary interpretability.
- Implement a Modular design with each module targeting a specific sub-problem, improving Scalability.
- Employ policy reuse by warehousing policies learned for sub-problems across tasks.
- If sufficient interaction data is available, employ data augmentation strategies for counterfactual scenarios using latent models.

## 6.2 Unsupervised RL

Unsupervised RL (Laskin et al., 2021) refers to the sub-field of behavior learning in RL, where an agent learns to interact with an environment without receiving explicit feedback or guidance in the form of rewards. Methods in this area can be characterized based on the nature of the metrics that are used to evaluate performance intrinsically (Srinivas & Abbeel, 2021). Knowledge-based methods define a self-supervised task by making predictions on some aspect of the environment (Pathak et al., 2017; Chen et al., 2022, 2022), Data-based methods maximize the state visitation entropy for exploring the environment (Hazan et al., 2019; Zhang et al., 2021b; Guo et al., 2021; Mutti et al., 2021, 2022), and Competence-based methods maximize the mutual information between the trajectories and space of learned skills (Mohamed & Rezende, 2015; Gregor et al., 2016; Baumli et al., 2021; Jiang et al., 2022; Zeng et al., 2022). The pre-training phase allows these methods to learn the underlying structure of data. However, this phase also requires large amounts of data and, thus, impacts the scalability of such methods for problems where the learned representations are not very useful. Consequently, such methods currently handle medium complexity problems, with the avenue of better scalability being a topic of further research.

Structural decompositions can help such methods by improving the pre-training phase's tractability and the fine-tuning phase's generality. Latent decompositions could help exploit structure in unlabeled data, while relational decompositions could add interpretability to the learned representations. Through augmentation, conditioning policies on specific parts of the state space can reduce the amount of data needed for fine-tuning. Additionally, understanding problem decomposition can simplify complex problems into more manageable sub-problems, effectively reducing the perceived problem complexity while incorporating such decomposition in external curricula for fine-tuning. Incorporating warehousing guided

by decompositions for competence-based methods can boost the fine-tuning process of the learned skills.

#### Unsupervised RL Patterns

- Use latent decompositions to extract structure from unlabeled data, reducing Data Dependency.
- Employ factored and modular decompositions and abstractions to manage scalability by focusing learning on different parts of the problem independently.
- Warehouse skills across different modular sub-problems to reuse solutions and enhance Generality.
- Manage Problem Complexity by leveraging problem decomposition to simplify the learning task and using decompositions for fine-tuning using curriculum learning.

# 6.3 Big Data and Foundation models in RL

Foundation models (Brown et al., 2020; OpenAI, 2023; Kirillov et al., 2023) refer to a paradigm where a large model is pre-trained on large and heterogeneous datasets and fine-tuned for specific tasks. These models are "foundational" in the sense that they can serve as the basis for a wide range of tasks, reducing the need for training separate models for each task from scratch.

Foundation models for RL come increasingly closer to becoming a reality. Such RL models would follow a similar concept of training a large model on various tasks, environments, and behaviors to be fine-tuned for specific downstream tasks. SMART (Sun et al., 2023), one of the current contenders for such models, follows this paradigm by using a self-supervised and control-centric objective that encourages the transformer-based model to capture control-relevant representation and demonstrates superior performance when used for fine-tuning. AdA (Bauer et al., 2023) trains an in-context learning agent on a vast distribution of tasks where the task factors are generated from a latent ruleset.

Given the pre-training paradigm, these methods are highly data-dependent in principle. However, incorporating large amounts of data can demonstrate scalability benefits by reducing fine-tuning costs for distributed applications. A natural question that arises is the role of Structured RL in the realm of end-end learning and big data. Even though such methods subscribe to an end-to-end paradigm, structural decompositions can benefit them differently.

Interpretability and Selection during Fine-tuning. Researchers can better understand the decomposability in the pre-trained models by categorizing methods based on how they incorporate structure. Consequently, this can guide the selection processes for fine-tuning methods depending on the tasks at hand. Passive learning from pre-trained models can benefit from better explanations about what parts of a fine-tuning task space might be suited for what kind of warmstarting strategies. Additionally, incorporating interpretability-oriented decompositions such as relational representations can help design more interpretable fine-tuning methods.

Task-Specific Architectures and Algorithms. Structural information can guide the development of novel architectures. With a better understanding of how different architectures and algorithms incorporate structural information, practitioners can more effectively

adapt existing methods or contribute to designing novel solutions tailored to their specific tasks. For example, Action Branching architectures might provide modular functionality in downstream tasks, especially suited for multi-task settings. On the other hand, representation bottlenecks might suit settings that deviate from each other by small changes in contextual features.

Improved Fine-Tuning and Transfer Learning. By understanding how to decompose tasks and incorporate structural information, foundational models can be fine-tuned more effectively for specific tasks or transferred to new tasks. The understanding of decompositions could guide how to structure the fine-tuning process or how to adapt the foundational model to a new task. By understanding how to incorporate structural information during fine-tuning, they can potentially achieve improved performance.

Benchmarking and Evaluation. By understanding the spectrum of decomposability and how various methods incorporate structure, we can create better benchmarks and evaluation protocols for foundational models. For instance, we can evaluate how well foundational models handle tasks of different decompositions and patterns of fine-tuning. Researchers can use this framework to design better evaluation protocols and benchmarks for foundational models. For practitioners, such benchmarks and evaluation protocols can guide the selection of models and algorithms for their specific tasks.

#### Foundation Model Patterns

- Use Factored or Relational abstractions on the pre-trained foundation model for state abstractions to manage high-dimensional state spaces and, thus, reduce data dependency.
- Condition the policy on additional task-specific information, such as goal information, representation of specific fine-tuning instructions, or control priors to improve scalability.
- Regularize the fine-tuning process to prevent catastrophic forgetting of useful features learned during pre-training.
- Maintain a warehouse of fine-tuned policies and value functions to help reuse previously learned skills and adapt them to new tasks, improving learning efficiency and generalization.
- Incorporate a curriculum of increasingly complex fine-tuning environments based on the agent's performance to help the agent gradually adapt the foundation model's knowledge to the specific RL task.
- Use explicit architectures that fine-tune different RL problem aspects, such as perception, policy learning, and value estimation.

#### 6.4 Partial observability and Big Worlds

In many real-world situations, the Markov property might not fully capture the dynamics of the environment (Whitehead & Lin, 1995; Cheung et al., 2020). This can happen in cases where the environment's state or the rewards depend on more than just the most recent state and action or if the agent cannot fully observe the state of the environment at each time step. In such situations, methods must deal with non-Markovian dynamics and partial observability.

**Abstractions.** Abstractions can play a crucial role in such situations, where structural decompositions using abstraction patterns can make methods more sample efficient. Often

used in options, temporal Abstractions allow the agent to make decisions over extended periods, thereby encapsulating potential temporal dependencies within these extended actions. This can effectively convert a non-Markovian problem into a Markovian one at the level of options. State Abstractions abstract away irrelevant aspects of the state and, thus, can sometimes ignore certain temporal dependencies, rendering the process Markovian at the level of the abstracted states. Thus, research into the role of decompositions in abstraction opens up possibilities to understand the dependencies between non-Markovian models and the kind of abstractions they use to solve problems with incomplete information. Abstraction can also simplify the observation space in POMDPs, reducing the complexity of the belief update process. The abstraction might involve grouping similar observations together, identifying higher-level features, or other simplifications. Abstractions can additionally allow us to break partial observability down into different types instead of always assuming the worst-case scenario. Utilizing such restricted assumptions on partial observability can help us build more specific algorithms and derive convergence and optimality guarantees for such scenarios.

Augmentations. Any additional information required, such as belief states or memory of past observations, can be used as abstractions or augmentations. This can also help with more efficient learning of transition models for planning. Hierarchical techniques that utilize optimization at different timescales can incorporate warehousing to reuse learned policies across various levels of abstraction. Environment generation patterns could also be used to generate a curriculum of increasingly complex tasks for the agent, starting with simpler MDPs and gradually introducing partial observability or other non-Markovian features.

Big worlds. As we extend the information content of the environment to its extremity, we delve into the realm of the big world hypothesis in RL (Javed, 2023), where the agent's environment is multiple orders of magnitude larger than the agent, and the agent cannot represent the optimal value function and policy even in the limit of infinite data. In such scenarios, the agent must make decisions under significant uncertainty, which presents several challenges, including exploration, generalization, and efficient learning. Even though the hypothesis suggests that incorporating side information might not be beneficial in learning the optimal policy and value in such scenarios, structural decomposition of large environments in different ways can allow benchmarking methods along different axes while allowing a deeper study into the performance of algorithms on parts of the environment that the agent has not yet experienced.

Modular decomposition can guide the agent's exploration process by helping the agent explore different parts of the environment independently. Incorporating modularity opens a gateway to novel methods and theoretical insights about the relationships between task decomposition, exploration, and learning efficiency in large environments. Relational decompositions can help the agent learn relationships between different entities, bolstering its ability to generalize to unseen parts of the environment. Finally, Structural information can be used to facilitate more efficient learning. For instance, in an auxiliary optimization pattern, the agent could learn faster by optimizing auxiliary tasks that are easier to learn or provide useful information about the environment's structure.

## Patterns for Partial Observability and Big Worlds

- Use temporal and state abstraction to abstract away temporal dependencies and non-Markovian
  aspects of the state. Utilize Modularity to tie these abstractions to learned primitives such as
  skills or options.
- Use memory more efficiently as an abstraction or augmentation for learned transition models.
- Warehouse policies and utilize them for optimization across timescales, such as in hierarchical methods, to make them more tractable.
- Utilize modular decompositions for guiding separate and parallel exploration mechanisms for different parts of the state space. Utilize relational abstractions to make this knowledge more interpretable.
- Utilize structure for task factorization to guide benchmarking methods along different axes of task complexity.

## 6.5 Automated RL

Automated RL (AutoRL) is a sub-field focused on methods to automate the process of designing and optimizing RL algorithms, including the agent's architecture, reward function, and other hyperparameters (Parker-Holder et al., 2022). Methods in AutoRL can be placed on a spectrum of automation, where on one end would be methods to select pipelines and on the other would be methods that try to discover new algorithms groundup in a data-driven manner (Oh et al., 2020). Techniques from the Automated Machine Learning literature (Hutter et al., 2019) then transfer to the RL setting, including algorithm selection (Laroche & Feraud, 2022), hyperparameter optimization (Li et al., 2019; Parker-Holder et al., 2020; Wan et al., 2022), dynamic configurations (Adriaensen et al., 2022), learned optimizers (Lan et al., 2023), and neural architecture search (Wan et al., 2022). Similarly, techniques from the Evolutionary optimization and Meta-Learning literature naturally transfer to this setting with methods aiming to meta-learn parts of the RL pipeline such as update rules (Oh et al., 2020), loss functions (Salimans et al., 2017; Kirsch et al., 2020), symbolic representations of algorithms (Alet et al., 2020; Co-Reyes et al., 2021; Luis et al., 2022), or concept drift (Lu et al., 2022). However, there are still many open questions in AutoRL, such as properties of hyperparameter landscapes in RL (Mohan et al., 2023), sound evaluation protocols (Eimer et al., 2023), stability of training due to the non-stationary learning task and non-deterministic data collection on the fly. Consequently, most of these methods suffer from a lack of scalability.

Algorithm Selection and Configuration. Depending on the decomposability of the problem at hand, different RL methods could be more appropriate. Structural decompositions can guide the selection process in AutoRL by suggesting appropriate types of decompositions based on the problem characteristics. Understanding how different decomposition types influence the performance of RL methods can bridge the gap between selection and configuration by helping researchers understand the level of abstraction needed for selection conditioned on the task, aiding in developing more efficient and targeted search algorithms. Decomposability can also guide ranking procedures, where methods that cater to different decomposability can be ranked differently, given a problem.

Hyperparameter Optimization. Parameters related to structural decomposition (e.g., the number of subtasks in a modular decomposition) could be part of the hyperparameter optimization process in AutoRL. Researchers can investigate the interplay between configuration spaces of hyperparameters and various structural decomposition-related parameters. For example, high decomposability might require different exploration rates or learning rates than a low decomposability problem. This could lead to novel insights and methods for more effective hyperparameter optimization in AutoRL. Practitioners can use this understanding to guide the hyperparameter optimization process in their AutoRL system. By tuning parameters related to the decomposition, they can potentially improve the performance of their RL agent.

#### AutoRL Patterns

- Use methods to perform a decomposability assessment of a problem. This can help guide algorithm selection for problems with different types of decomposability.
- Expedite the hyperparameter search by abstracting away task-irrelevant aspects.
- Warehouse to reuse learned policy and value functions for landmarking performances of algorithms similar to the one being optimized.
- Incorporate modularity information in the form of goals and task hierarchies in the search process.
- Structure neural architecture search-space using decomposability in the problem.

#### 6.6 Meta-Reinforcement Learning

Meta-Reinforcement Learning, while having overlaps with AutoRL, is a field in and of itself (Beck et al., 2023) that focuses on training agents to adapt and learn new tasks or environments quickly. The general Meta-RL setup involves a bi-level optimization procedure where an agent learns a set of parameters by training on a distribution of tasks or environments that help it adapt and perform well on new, unseen tasks that share some form of overlap with the training tasks. Beck et al. (2023) outline different problem settings in Meta-RL based on the kind of feedback (supervised, unsupervised, rewards) that is provided to the agent during the training and adaptation phases. We particularly refer to the standard setting where extrinsic rewards act as feedback during the training and adaptation phases. However, decompositions can also be useful for other settings similar to those discussed in other sections.

Task Decompositions. Depending on the meta-task's decomposability, different task decomposition approaches could be employed to guide the meta-learning process. Consequently, understanding how task decomposition affects Meta-RL can guide the development of more effective meta-learning algorithms. It might also lead to new insights on balancing learning between different subtasks. By identifying suitable decompositions, practitioners can set up their system to learn in a way that is more aligned with the structure of the tasks, potentially leading to improved performance.

**Adaptation Strategies.** Decompositions could inform the way a Meta-RL agent adapts to a new task. For instance, if the new task is highly decomposable, a modular adaptation strategy could be more appropriate by guiding the agent to an appropriate latent space of

the new task. Thus, our framework of decomposability can inspire new research into how the task's decomposition, f can guide adaptation strategies in Meta-RL. This could lead to novel methods or theories on adapting to new tasks more effectively based on their structure.

## Meta-RL Patterns

- Use decompositions for abstracting task distributions, which can be integrated into the adaptation process.
- Compartmentalize the learning process into modules for highly decomposable problems. These
  modules can serve as abstract configurations for the meta-level and, thus, make the outer loop
  more tractable
- Learn and warehouse models geared towards specific task clusters for different decomposability types to guide data augmentation during the adaptation phase.
- Utilize decomposability to design learning curricula based on abstract types of tasks to train the warmstarting configurations

## 7. Conclusion and Future Work

Understanding the intricacies of Reinforcement Learning (RL) 's complexities is challenging, exacerbated by the divergent methodologies employed across different problem domains. This fragmentation hinders the development of unifying principles and consistent practices in RL. To address this critical gap, we propose an innovative framework to understand different methods of effectively integrating the inherent structure of learning problems into RL algorithms. Our work serves as a pivotal step towards consolidating the multifaceted aspects of RL, ushering in a design pattern perspective for this domain.

We first conceptualized structure as side information about the decomposability of a learning problem and corresponding solutions. We have categorized decomposability into four distinct archetypes - latent, factored, relational, and modular. This classification delineates a spectrum that establishes insightful connections with existing literature, elucidating the diverse influence of structure within RL.

We then presented seven key patterns following a thorough analysis of the RL land-scape - abstraction, augmentation, auxiliary optimization, auxiliary model, warehousing, environment generation, and explicitly designed patterns. These patterns represent strategic approaches for the incorporation of structural knowledge into RL. Although our framework provides a comprehensive starting point, we acknowledge that these patterns are not exhaustive. We envisage this as an impetus for researchers to refine and develop new patterns, thereby expanding the repertoire of design patterns in RL.

In conclusion, our work offers a pattern-centric perspective on RL, underlining the critical role of structural decompositions in shaping both present and future paradigms. By promoting this perspective, we aim to stimulate a new wave of research in RL, enriched by a deeper and more structured understanding of the field. While our proposed framework is a novel contribution, it should be viewed as an initial step in an ongoing process. We anticipate and encourage further development and refinement of our framework and eagerly await the emergence of new, innovative patterns that will undoubtedly shape the future of RL.

## Acknowledgments

The authors thank Robert Kirk and Rohan Chitnis for their discussion and comments on drafts of this work. We would also like to thank Vincent François-Lavet, Khimya Khetrapal, and Rishabh Aggarwal for providing additional relevant references in the literature.

## References

- Abdulhai, M., Kim, D., Riemer, M., Liu, M., Tesauro, G., & How, J. (2022). Context-specific representation abstraction for deep option learning. In Sycara et al. (Sycara, Honavar, & Spaan, 2022).
- Abel, D., Hershkowitz, D., Barth-Maron, G., Brawner, S., O'Farrell, K., MacGlashan, J., & Tellex, S. (2015). Goal-based action priors. In Proceedings of the Twenty-Fifth International Conference on Automated Planning and Scheduling, (ICAPS'15).
- Abel, D., Umbanhowar, N., Khetarpal, K., Arumugam, D., Precup, D., & Littman, M. (2020). Value preserving state-action abstractions. In *Proceedings of the 23rd International Conference on Artificial Intelligence and Statistics, (AISTATS'20)*, pp. 1639–1650.
- Adjodah, D., Klinger, T., & Joseph, J. (2018). Symbolic relation networks for reinforcement learning. In *Proceedings of the Workshop on Relational Representation Learning in Conference on Neural Information Processing Systems (NeurIPS)*.
- Adriaensen, S., Biedenkapp, A., Shala, G., Awad, N., Eimer, T., Lindauer, M., & Hutter, F. (2022). Automated dynamic algorithm configuration. *Journal of Artificial Intelligence Research (JAIR)*, 75, 1633–1699.
- Agarwal, R., Machado, M., Castro, P., & Bellemare, M. (2021). Contrastive behavioral similarity embeddings for generalization in reinforcement learning. In *Proceedings of the Ninth International Conference on Learning Representations, (ICLR'21)*.
- Alabdulkarim, A., & Riedl, M. (2022). Experiential explanations for reinforcement learning. *CoRR*, *abs/2210.04723*.
- Alet, F., Schneider, M., Lozano-Pérez, T., & Kaelbling, L. (2020). Meta-learning curiosity algorithms. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR'20)*. OpenReview.net.
- Allen, C., Parikh, N., Gottesman, O., & Konidaris, G. (2021). Learning markov state abstractions for deep reinforcement learning. In Ranzato et al. (Ranzato, Beygelzimer, Nguyen, Liang, Vaughan, & Dauphin, 2021).
- Amin, S., Gomrokchi, M., Aboutalebi, H., Satija, H., & Precup, D. (2021a). Locally persistent exploration in continuous control tasks with sparse rewards.. In Meila, & Zhang (Meila & Zhang, 2021).
- Amin, S., Gomrokchi, M., Satija, H., van Hoof, H., & Precup, D. (2021b). A survey of exploration methods in reinforcement learning. *CoRR*, *abs/2109.00157*.
- Andersen, G., & Konidaris, G. (2017). Active exploration for learning symbolic representations.. In Guyon et al. (Guyon, von Luxburg, Bengio, Wallach, Fergus, Vishwanathan, & Garnett, 2017).

- Andreas, J., Klein, D., & Levine, S. (2018). Learning with latent language. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*,.
- Azizzadenesheli, K., Lazaric, A., & Anandkumar, A. (2016). Reinforcement learning in rich-observation mdps using spectral methods. *CoRR*, *abs/1611.03907*.
- Bacon, P., Harb, J., & Precup, D. (2017). The option-critic architecture. In S.Singh, & Markovitch, S. (Eds.), Proceedings of the Thirty-First Conference on Artificial Intelligence (AAAI'17). AAAI Press.
- Baheri, A. (2020). Safe reinforcement learning with mixture density network: A case study in autonomous highway driving. *CoRR*, *abs/2007.01698*.
- Bain, M., & Sammut, C. (1995). A framework for behavioural cloning. In Furukawa, K., Michie, D., & Muggleton, S. (Eds.), Machine Intelligence 15, Intelligent Agents [St. Catherine's College, Oxford, UK, July 1995], pp. 103–129. Oxford University Press.
- Balaji, B., Christodoulou, P., Jeon, B., & Bell-Masterson, J. (2020). Factored: Leveraging factored graphs for deep reinforcement learning. In *NeurIPS Deep Reinforcement Learning Workshop*.
- Bapst, V., Sanchez-Gonzalez, A., Doersch, C., Stachenfeld, K., Kohli, P., Battaglia, P., & Hamrick, J. (2019). Structured agents for physical construction.. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).
- Barreto, A., Borsa, D., Hou, S., Comanici, G., Aygün, E., Hamel, P., Toyama, D., Hunt, J., Mourad, S., Silver, D., & Precup, D. (2019). The option keyboard: Combining skills in reinforcement learning. In Wallach et al. (Wallach, Larochelle, Beygelzimer, d'Alche Buc, Fox, & Garnett, 2019).
- Barreto, A., Borsa, D., Quan, J., Schaul, T., Silver, D., Hessel, M., Mankowitz, D., Zidek, A., & Munos, R. (2018). Transfer in deep reinforcement learning using successor features and generalised policy improvement.. In Dy, & Krause (Dy & Krause, 2018).
- Barreto, A., Dabney, W., Munos, R., Hunt, J., Schaul, T., van Hasselt, H., & Silver, D. (2017). Successor features for transfer in reinforcement learning. In Guyon et al. (Guyon et al., 2017).
- Bauer, J., Baumli, K., Baveja, S., Behbahani, F., Bhoopchand, A., Bradley-Schmieg, N., Chang, M., Clay, N., Collister, A., Dasagi, V., Gonzalez, L., Gregor, K., Hughes, E., Kashem, S., Loks-Thompson, M., Openshaw, H., Parker-Holder, J., Pathak, S., Nieves, N., Rakicevic, N., Rocktäschel, T., Schroecker, Y., Sygnowski, J., Tuyls, K., York, S., Zacherl, A., & Zhang, L. (2023). Human-timescale adaptation in an open-ended task space. CoRR, abs/2301.07608.
- Baumli, K., Warde-Farley, D., Hansen, S., & Mnih, V. (2021). Relative variational intrinsic control.. In Yang et al. (Yang, Leyton-Brown, & Mausam, 2021).
- Beck, J., Vuorio, R., Liu, E., Xiong, Z., Zintgraf, L., Finn, C., & Whiteson, S. (2023). A survey of meta-reinforcement learning. *CoRR*, *abs/2301.08028*.
- Bellman, R. (1954). Some applications of the theory of dynamic programming A review. *Oper. Res.*, 2(3), 275–288.

- Belogolovsky, S., Korsunsky, P., Mannor, S., Tessler, C., & Zahavy, T. (2021). Inverse reinforcement learning in contextual mdps. *Mach. Learn.*, 110(9), 2295–2334.
- Bengio, S., Wallach, H., Larochelle, H., Grauman, K., Cesa-Bianchi, N., & Garnett, R. (Eds.). (2018). Proceedings of the 31st International Conference on Advances in Neural Information Processing Systems (NeurIPS'18). Curran Associates.
- Benjamins, C., Eimer, T., Schubert, F., Mohan, A., Döhler, S., Biedenkapp, A., Rosenhahn, B., Hutter, F., & Lindauer, M. (2023). Contextualize me the case for context in reinforcement learning. *Transactions on Machine Learning Research*, 2835-8856.
- Bewley, T., & Lecune, F. (2022). Interpretable preference-based reinforcement learning with tree-structured reward functions. In 21st International Conference on Autonomous Agents and Multiagent Systems, AAMAS 2022, Auckland, New Zealand, May 9-13, 2022. International Foundation for Autonomous Agents and Multiagent Systems (IFAAMAS).
- Beyret, B., Shafti, A., & Faisal, A. (2019). Dot-to-dot: Explainable hierarchical reinforcement learning for robotic manipulation. In *International Conference on Intelligent Robots and Systems*, (IROS'19), pp. 5014–5019. IEEE.
- Bhargava, P., Chitnis, R., Geramifard, A., Sodhani, S., & Zhang, A. (2023). Sequence modeling is a robust contender for offline reinforcement learning. *CoRR*, *abs/2305.14550*.
- Bhatt, V., Tjanaka, B., Fontaine, M., & Nikolaidis, S. (2022). Deep surrogate assisted generation of environments. In *Proceedings of the 35th International Conference on Advances in Neural Information Processing Systems (NeurIPS'22)*.
- Biza, O., Kipf, T., Klee, D., Platt, R., van de Meent, J., & Wong, L. (2022a). Factored world models for zero-shot generalization in robotic manipulation. In arXiv preprint arXiv:2202.05333.
- Biza, O., Platt, R., van de Meent, J., Wong, L., & Kipf, T. (2022b). Binding actions to objects in world models. In arXiv preprint arXiv:2204.13022.
- Borsa, D., Barreto, A., Quan, J., Mankowitz, D., van Hasselt, H., Munos, R., Silver, D., & Schaul, T. (2019). Universal successor features approximators. In *Proceedings of the Seventh International Conference on Learning Representations (ICLR'19)*.
- Borsa, D., Graepel, T., & Shawe-Taylor, J. (2016). Learning shared representations in multi-task reinforcement learning. CoRR, abs/1603.02041.
- Boutilier, C., Cohen, A., Hassidim, A., Mansour, Y., Meshi, O., Mladenov, M., & Schuurmans, D. (2018). Planning and learning with stochastic action sets.. In Lang (Lang, 2018).
- Boutilier, C., Dearden, R., & Goldszmidt, M. (2000). Stochastic dynamic programming with factored representations. *Artificial Intelligence*, 121(1-2), 49–107.
- Brockman, G., Cheung, V., Pettersson, L., Schneider, J., Schulman, J., Tang, J., & Zaremba, W. (2016). OpenAI gym. In arxiv preprint arXiv:1606.01540.
- Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J., Dhariwal, P., Neelakantan, A.,
  Shyam, P., Sastry, G., Askell, A., Agarwal, S., Herbert-Voss, A., Krueger, G., Henighan,
  T., Child, R., Ramesh, A., Ziegler, D., Wu, J., Winter, C., Hesse, C., Chen, M., Sigler,
  E., Litwin, M., Gray, S., Chess, B., Clark, J., Berner, C., McCandlish, S., Radford,

- A., Sutskever, I., & Amodei, D. (2020). Language models are few-shot learners.. In Larochelle et al. (Larochelle, Ranzato, Hadsell, Balcan, & Lin, 2020), pp. 1877–1901.
- Brunskill, E., & Li, L. (2013). Sample complexity of multi-task reinforcement learning. In Nicholson, A., & Smyth, P. (Eds.), *Proceedings of the 29th conference on Uncertainty in Artificial Intelligence (UAI'13)*. AUAI Press.
- Buchholz, P., & Scheftelowitsch, D. (2019). Computation of weighted sums of rewards for concurrent mdps. *Math. Methods Oper. Res.*, 89(1), 1–42.
- Buesing, L., Weber, T., Zwols, Y., Heess, N., Racanière, S., Guez, A., & Lespiau, J. (2019). Woulda, coulda, shoulda: Counterfactually-guided policy search. In *Proceesings of the Seventh International Conference on Learning Representations (ICLR'19)*. OpenReview.net.
- Burgess, C., Matthey, L., Watters, N., Kabra, R., Higgins, I., Botvinick, M., & Lerchner, A. (2019). Monet: Unsupervised scene decomposition and representation. *CoRR*, *abs/1901.11390*.
- Castro, P., Kastner, T., Panangaden, P., & Rowland, M. (2021). Mico: Improved representations via sampling-based state similarity for markov decision processes.. In Ranzato et al. (Ranzato et al., 2021).
- Castro, P., Kastner, T., Panangaden, P., & Rowland, M. (2023). A kernel perspective on behavioural metrics for markov decision processes. In *Transactions on Machine Learning Research*.
- Chandak, Y., Theocharous, G., Kostas, J., Jordan, S., & Thomas, P. (2019). Learning action representations for reinforcement learning. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).
- Chaudhuri, K., Jegelka, S., Song, L., Szepesvári, C., Niu, G., & Sabato, S. (Eds.). (2022). Proceedings of the 39th International Conference on Machine Learning (ICML'22), Vol. 162 of Proceedings of Machine Learning Research. PMLR.
- Chaudhuri, K., & Salakhutdinov, R. (Eds.). (2019). Proceedings of the 36th International Conference on Machine Learning (ICML'19), Vol. 97. Proceedings of Machine Learning Research.
- Chen, C., Gao, Z., Xu, K., Yang, S., Li, Y., Ding, B., Feng, D., & Wang, H. (2022). Nuclear norm maximization based curiosity-driven learning. *CoRR*, *abs/2205.10484*.
- Chen, C., Hu, S., Nikdel, P., Mori, G., & Savva, M. (2020). Relational graph learning for crowd navigation. In 2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). IEEE.
- Chen, C., Wan, T., Shi, P., Ding, B., Gao, Z., & Feng, D. (2022). Uncertainty estimation based intrinsic reward for efficient reinforcement learning. In 2022 IEEE International Conference on Joint Cloud Computing (JCC), pp. 1–8.
- Chen, L., Lu, K., Rajeswaran, A., Lee, K., Grover, A., Laskin, M., Abbeel, P., Srinivas, A., & Mordatch, I. (2021). Decision transformer: Reinforcement learning via sequence modeling. In Ranzato et al. (Ranzato et al., 2021).

- Cheung, W., Simchi-Levi, D., & Zhu, R. (2020). Reinforcement learning for non-stationary markov decision processes: The blessing of (more) optimism. In *icml20*.
- Christodoulou, P., Lange, R., Shafti, A., & Faisal, A. (2019). Reinforcement learning with structured hierarchical grammar representations of actions. *CoRR*, *abs/1910.02876*.
- Chu, Z., & Wang, H. (2023). Meta-reinforcement learning via exploratory task clustering. In arXiv preprint arXiv:2302.07958.
- Co-Reyes, J., Miao, Y., Peng, D., Real, E., Le, Q., Levine, S., Lee, H., & Faust, A. (2021). Evolving reinforcement learning algorithms. In *Proceedings of the Ninth International Conference on Learning Representations (ICLR'20)*. OpenReview.net.
- Dayan, P. (1993). Improving generalization for temporal difference learning: The successor representation. *Neural Comput.*, 5(4), 613–624.
- der Pol, E. V., Worrall, D., van Hoof, H., Oliehoek, F., & Welling, M. (2020). Mdp homomorphic networks: Group symmetries in reinforcement learning.. In Larochelle et al. (Larochelle et al., 2020).
- D'Eramo, C., Tateo, D., Bonarini, A., Restelli, M., & J. Peters, J. (2020). Sharing knowledge in multi-task deep reinforcement learning. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR'20)*.
- Devin, C., Geng, D., Abbeel, P., Darrell, T., & Levine, S. (2019). Plan arithmetic: Compositional plan vectors for multi-task control. *CoRR*, *abs/1910.14033*.
- Devin, C., Gupta, A., Darrell, T., Abbeel, P., & Levine, S. (2017). Learning modular neural network policies for multi-task and multi-robot transfer. In *IEEE International Conference on Robotics and Automation (ICRA)*.
- Ding, W., Lin, H., Li, B., & Zhao, D. (2022). Generalizing goal-conditioned reinforcement learning with variational causal reasoning. In *Proceedings of the 35th International Conference on Advances in Neural Information Processing Systems (NeurIPS'22)*.
- Diuk, C., Cohen, A., & Littman, M. (2008). An object-oriented representation for efficient reinforcement learning. In Cohen, W., McCallum, A., & Roweis, S. (Eds.), *Proceedings of the 25th International Conference on Machine Learning (ICML'08)*. Omnipress.
- Du, S., Krishnamurthy, A., Jiang, N., Agarwal, A., Dudík, M., & Langford, J. (2019). Provably efficient RL with rich observations via latent state decoding.. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).
- Dy, J., & Krause, A. (Eds.). (2018). Proceedings of the 35th International Conference on Machine Learning (ICML'18), Vol. 80. Proceedings of Machine Learning Research.
- Dzeroski, S., Raedt, L. D., & Driessens, K. (2001). Relational reinforcement learning. Machine Learning Journal, 43(1/2), 7–52.
- Ecoffet, A., Huizinga, J., Lehman, J., Stanley, K., & Clune, J. (2021). First return, then explore. *Nature*, 590 (7847), 580–586.
- Eimer, T., Lindauer, M., & Raileanu, R. (2023). Hyperparameters in reinforcement learning and how to tune them. In *Proceedings of the International Conference on Machine Learning (ICML'23)*.

- Eysenbach, B., Gupta, A., Ibarz, J., & Levine, S. (2019). Diversity is all you need: Learning skills without a reward function. In *Proceedings of the Seventh International Conference on Learning Representations (ICLR'19)*.
- Fern, A., Yoon, S., & Givan, R. (2006). Approximate policy iteration with a policy language bias: Solving relational markov decision processes. *Journal of Artificial Intelligence Research*, 25, 75–118.
- Florensa, C., Duan, Y., & Abbeel, P. (2017). Stochastic neural networks for hierarchical reinforcement learning. In *Proceedings of Fifth the International Conference on Learning Representations (ICLR'17)*.
- Fox, R., Pakman, A., & Tishby, N. (2016). Taming the noise in reinforcement learning via soft updates. In Ihler, A., & Janzing, D. (Eds.), *Proceedings of the 32nd conference on Uncertainty in Artificial Intelligence (UAI'16)*. AUAI Press.
- Fu, X., Yang, G., Agrawal, P., & Jaakkola, T. (2021). Learning task informed abstractions.. In Meila, & Zhang (Meila & Zhang, 2021).
- Furelos-Blanco, D., Law, M., Jonsson, A., Broda, K., & Russo, A. (2021). Induction and exploitation of subgoal automata for reinforcement learning. *J. Artif. Intell. Res.*, 70, 1031–1116.
- Gallouedec, Q., & Dellandrea, E. (2023). Cell-free latent go-explore. In *Proceedings of the* 40th International Conference on Machine Learning (ICML'23).
- Garcia, J., & Fernandez, F. (2015). A comprehensive survey on safe reinforcement learning. Journal of Machine Learning Research, 16, 1437–1480.
- Garg, S., Bajpai, A., & Mausam (2020). Symbolic network: Generalized neural policies for relational mdps.. In III, & Singh (III & Singh, 2020).
- Garnelo, M., Arulkumaran, K., & Shanahan, M. (2016). Towards deep symbolic reinforcement learning. In  $arXiv\ preprint\ arXiv:1609.05518$ .
- Gasse, M., Grasset, D., Gaudron, G., & Oudeyer, P. (2021). Causal reinforcement learning using observational and interventional data. In arXiv preprint arXiv:2106.14421.
- Gaya, J., Doan, T., Caccia, L., Soulier, L., Denoyer, L., & Raileanu, R. (2022a). Building a subspace of policies for scalable continual learning. In arXiv preprint arXiv:2211.10445.
- Gaya, J., Soulier, L., & Denoyer, L. (2022b). Learning a subspace of policies for online adaptation in reinforcement learning. In *Proceedings of the Tenth International Conference on Learning Representations (ICLR'22)*.
- Gehring, J., Synnaeve, G., Krause, A., & Usunier, N. (2021). Hierarchical skills for efficient exploration.. In Ranzato et al. (Ranzato et al., 2021).
- Geißer, F., Speck, D., & Keller, T. (2020). Trial-based heuristic tree search for mdps with factored action spaces. In *Proceedings of the International Symposium on Combinatorial Search*.
- Gelada, C., Kumar, S., Buckman, J., Nachum, O., & Bellemare, M. (2019). Deepmdp: Learning continuous latent space models for representation learning. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).

- Ghorbani, M., Hosseini, R., Shariatpanahi, S., & Ahmadabadi, M. (2020). Reinforcement learning with subspaces using free energy paradigm. In arXiv preprint arXiv:2012.07091.
- Gillen, S., & Byl, K. (2021). Explicitly encouraging low fractional dimensional trajectories via reinforcement learning. In *Conference on Robot Learning*, pp. 2137–2147. PMLR.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.
- Goyal, A., Lamb, A., Hoffmann, J., Sodhani, S., Levine, S., Bengio, Y., & Schölkopf, B. (2021). Recurrent independent mechanisms. In Proceedings of the Ninth International Conference on Learning Representations (ICLR'21).
- Goyal, A., Sodhani, S., Binas, J., Peng, X., Levine, S., & Bengio, Y. (2020). Reinforcement learning with competitive ensembles of information-constrained primitives. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR'20)*.
- Gregor, K., Rezende, D., & Wierstra, D. (2016). Variational intrinsic control. *CoRR*, *abs/1611.07507*.
- Guestrin, C., Koller, D., Gearhart, C., & Kanodia, N. (2003a). Generalizing plans to new environments in relational mdps. In Gottlob, G., & Walsh, T. (Eds.), *Proceedings of the 18th International Joint Conference on Artificial Intelligence (IJCAI'03)*.
- Guestrin, C., Koller, D., Parr, R., & Venkataraman, S. (2003b). Efficient solution algorithms for factored mdps. *Journal of Artificial Intelligence Research*, 19, 399–468.
- Guo, J., Gong, M., & Tao, D. (2022). A relational intervention approach for unsupervised dynamics generalization in model-based reinforcement learning. In *Proceedings of* the Ninth International Conference on Learning Representations (ICLR'21). OpenReview.net.
- Guo, Z., Azar, M. G., Saade, A., Thakoor, S., Piot, B., Pires, B. Á., Valko, M., Mesnard, T., Lattimore, T., & Munos, R. (2021). Geometric entropic exploration. CoRR, abs/2101.02055.
- Gupta, A., Devin, C., Liu, Y., Abbeel, P., & Levine, S. (2017). Learning invariant feature spaces to transfer skills with reinforcement learning. In *Proceedings of the Fifth International Conference on Learning Representations (ICLR'17)*.
- Gupta, A., Mendonca, R., Liu, Y., Abbeel, P., & Levine, S. (2018). Meta-reinforcement learning of structured exploration strategies.. In Bengio et al. (Bengio, Wallach, Larochelle, Grauman, Cesa-Bianchi, & Garnett, 2018).
- Gur, I., Jaques, N., Miao, Y., Choi, J., Tiwari, M., Lee, H., & Faust, A. (2021). Environment generation for zero-shot compositional reinforcement learning.. In Ranzato et al. (Ranzato et al., 2021).
- Guyon, I., von Luxburg, U., Bengio, S., Wallach, H., Fergus, R., Vishwanathan, S., & Garnett, R. (Eds.). (2017). Proceedings of the 30th International Conference on Advances in Neural Information Processing Systems (NeurIPS'17). Curran Associates.
- Haarnoja, T., Hartikainen, K., Abbeel, P., & Levine, S. (2018a). Latent space policies for hierarchical reinforcement learning. In Dy, & Krause (Dy & Krause, 2018).

- Haarnoja, T., Pong, V., Zhou, A., Dalal, M., Abbeel, P., & Levine, S. (2018b). Composable deep reinforcement learning for robotic manipulation. In 2018 IEEE International Conference on Robotics and Automation (ICRA'18).
- Hafner, D., Lillicrap, T., Ba, J., & Norouzi, M. (2020). Dream to control: Learning behaviors by latent imagination.. In III, & Singh (III & Singh, 2020).
- Hafner, D., Pasukonis, J., Ba, J., & Lillicrap, T. (2023). Mastering diverse domains through world models. In arXiv preprint arXiv:2301.04104.
- Hallak, A., Castro, D. D., & Mannor, S. (2015). Contextual markov decision processes. CoRR, abs/1502.02259.
- Hansen-Estruch, P., Zhang, A., Nair, A., Yin, P., & Levine, S. (2022). Bisimulation makes analogies in goal-conditioned reinforcement learning.. In Chaudhuri et al. (Chaudhuri, Jegelka, Song, Szepesvári, Niu, & Sabato, 2022).
- Harutyunyan, A., Dabney, W., Borsa, D., Heess, N., Munos, R., & Precup, D. (2019). The termination critic. In Chaudhuri, K., & Sugiyama, M. (Eds.), The 22nd International Conference on Artificial Intelligence and Statistics, AISTATS 2019, 16-18 April 2019, Naha, Okinawa, Japan, Vol. 89 of Proceedings of Machine Learning Research, pp. 2231–2240. PMLR.
- Hausman, K., Springenberg, J., Wang, Z., Heess, N., & Riedmiller, M. (2018). Learning an embedding space for transferable robot skills. In *Proceedings of the Sixth International* Conference on Learning Representations (ICLR'18).
- Hazan, E., Kakade, S., Singh, K., & van Soest, A. (2019). Provably efficient maximum entropy exploration.. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).
- Heess, N., Wayne, G., Tassa, Y., Lillicrap, T., Riedmiller, M., & Silver, D. (2016). Learning and transfer of modulated locomotor controllers. In arXiv preprint arXiv:1610.05182.
- Henaff, M., Raileanu, R., Jiang, M., & Rocktäschel, T. (2022). Exploration via elliptical episodic bonuses. In *neurips22*.
- Higgins, I., Pal, A., Rusu, A., Matthey, L., Burgess, C., Pritzel, A., Botvinick, M., Blundell,
  C., & Lerchner, A. (2017). Darla: Improving zero-shot transfer in reinforcement
  learning.. In Precup, & Teh (Precup & Teh, 2017).
- Hofer, S. (2017). On Decomposability in Robot Reinforcement Learning. Technische University of Berlin (Germany).
- Hong, Z., Yang, G., & Agrawal, P. (2022). Bilinear value networks. CoRR, abs/2204.13695.
- Hu, Y., & Montana, G. (2019). Skill transfer in deep reinforcement learning under morphological heterogeneity. In arXiv preprint arXiv:1908.05265.
- Huang, W., Mordatch, I., & Pathak, D. (2020). One policy to control them all: Shared modular policies for agent-agnostic control. In III, & Singh (III & Singh, 2020).
- Hutter, F., Kotthoff, L., & Vanschoren, J. (Eds.). (2019). Automated Machine Learning: Methods, Systems, Challenges. Springer. Available for free at http://automl.org/book.

- Icarte, R., Klassen, T., Valenzano, R., & McIlraith, S. (2022). Reward machines: Exploiting reward function structure in reinforcement learning. J. Artif. Intell. Res., 73, 173–208.
- III, H. D., & Singh, A. (Eds.). (2020). Proceedings of the 37th International Conference on Machine Learning (ICML'20), Vol. 98. Proceedings of Machine Learning Research.
- Illanes, L., Yan, X., Icarte, R., & McIlraith, S. (2020). Symbolic plans as high-level instructions for reinforcement learning. In *Proceedings of the International Conference on Automated Planning and Scheduling*.
- Innes, C., & Lascarides, A. (2020). Learning factored markov decision processes with unawareness. In Peters, J., & Sontag, D. (Eds.), *Proceedings of The 36th Uncertainty in Artificial Intelligence Conference (UAI'20)*. PMLR.
- Islam, R., Zang, H., Goyal, A., Lamb, A., Kawaguchi, K., Li, X., Laroche, R., Bengio, Y., & Combes, R. (2022). Discrete factorial representations as an abstraction for goal conditioned reinforcement learning. In arXiv preprint arXiv:2211.00247.
- Jain, A., Khetarpal, K., & Precup, D. (2021a). Safe option-critic: Learning safety in the option-critic architecture. The Knowledge Engineering Review, 36, e4.
- Jain, A., Kosaka, N., Kim, K., & Lim, J. (2021b). Know your action set: Learning action relations for reinforcement learning. In Meila, & Zhang (Meila & Zhang, 2021).
- Jain, A., Szot, A., & Lim, J. (2020). Generalization to new actions in reinforcement learning.. In III, & Singh (III & Singh, 2020).
- Janisch, J., Pevny, T., & Lisy, V. (2020). Symbolic relational deep reinforcement learning based on graph neural networks. In arXiv preprint arXiv:2009.12462.
- Javed, K. (2023). The big world hypothesis and its ramifications on reinforcement learning.
- Jiang, N. (2018). Notes on state abstractions..
- Jiang, Y., Shane, S. G., Murphy, K., & Finn, C. (2019). Language as an abstraction for hierarchical deep reinforcement learning. In Wallach et al. (Wallach et al., 2019).
- Jiang, Z., Gao, J., & Chen, J. (2022). Unsupervised skill discovery via recurrent skill training. In neurips22.
- Jonschkowski, R., Höfer, S., & Brock, O. (2015). Patterns for learning with side information. In arXiv preprint arXiv:1511.06429.
- Joshi, S., & Khardon, R. (2011). Probabilistic relational planning with first order decision diagrams. *Journal of Artificial Intelligence Research*, 41, 231–266.
- Kaiser, M., Otte, C., Runkler, T., & Ek, C. (2019). Interpretable dynamics models for data-efficient reinforcement learning. In *Proceedings of the 27th European Symposium on Artificial Neural Networks (ESANN'19)*.
- Kakade, S. (2003). On the Sample Complexity of Reinforcement Learning. University of London, University College London (United Kingdom).
- Kaplanis, C., Shanahan, M., & Clopath, C. (2019). Policy consolidation for continual reinforcement learning. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).

- Karia, R., & Srivastava, S. (2022). Relational abstractions for generalized reinforcement learning on symbolic problems. In arXiv preprint arXiv:2204.12665.
- Kearns, M., & Koller, D. (1999). Efficient reinforcement learning in factored mdps. In Dean, T. (Ed.), Proceedings of the 16th International Joint Conference on Artificial Intelligence (IJCAI'99). Morgan Kaufmann Publishers.
- Khamassi, M., Velentzas, G., Tsitsimis, T., & Tzafestas, C. (2017). Active exploration and parameterized reinforcement learning applied to a simulated human-robot interaction task. In *First IEEE International Conference on Robotic Computing (IRC'17)*, pp. 28–35. IEEE Computer Society.
- Khetarpal, K., Ahmed, Z., Comanici, G., Abel, D., & Precup, D. (2020). What can i do here? a theory of affordances in reinforcement learning.. In III, & Singh (III & Singh, 2020).
- Khetarpal, K., Ahmed, Z., Comanici, G., & Precup, D. (2021). Temporally abstract partial models.. In Ranzato et al. (Ranzato et al., 2021).
- Khetarpal, K., Klissarov, M., Chevalier-Boisvert, M., Bacon, P., & Precup, D. (2020). Options of interest: Temporal abstraction with interest functions.. In Rossi et al. (Rossi, Conitzer, & Sha, 2020).
- Kim, K., & Dean, T. (2002). Solving factored mdps with large action space using algebraic decision diagrams. In *Trends in Artificial Intelligence*.
- Kipf, T., van der Pol, E., & Welling, M. (2020). Contrastive learning of structured world models. In *Proceedings of the Eighth International Conference on Learning Representations* (ICLR'20).
- Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A., Lo, W., Dollár, P., & Girshick, R. (2023). Segment anything. *CoRR*, abs/2304.02643.
- Kirk, R., Zhang, A., Grefenstette, E., & Rocktäschel, T. (2023). A survey of zero-shot generalisation in deep reinforcement learning. *Journal of Artificial Intelligence Research*, 76, 201–264.
- Kirsch, L., van Steenkiste, S., & Schmidhuber, J. (2020). Improving generalization in meta reinforcement learning using learned objectives. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR'20)*. OpenReview.net.
- Klissarov, M., & Machado, M. (2023). Deep laplacian-based options for temporally-extended exploration. In *Proceedings of the 40th International Conference on Machine Learning (ICML'23)*.
- Kokel, H., Manoharan, A., Natarajan, S., Ravindran, B., & Tadepalli, P. (2021). Reprel: Integrating relational planning and reinforcement learning for effective abstraction. In *Proceedings of the International Conference on Automated Planning and Scheduling*.
- Koller, D., & Parr, R. (1999). Computing factored value functions for policies in structured mdps. In IJCAI.
- Kooi, J., Hoogendoorn, M., & François-Lavet, V. (2022). Disentangled (un)controllable features. *CoRR*, *abs/2211.00086*.

- Kulkarni, T., Narasimhan, K., Saeedi, A., & Tenenbaum, J. (2016). Hierarchical deep reinforcement learning: Integrating temporal abstraction and intrinsic motivation. In Lee, D., Sugiyama, M., von Luxburg, U., Guyon, I., & Garnett, R. (Eds.), Proceedings of the 29th International Conference on Advances in Neural Information Processing Systems (NeurIPS'16). Curran Associates.
- Kumar, A., Zhou, A., Tucker, G., & Levine, S. (2020). Conservative q-learning for offline reinforcement learning. In Larochelle et al. (Larochelle et al., 2020).
- Kumar, S., Correa, C., Dasgupta, I., Marjieh, R., Hu, M., Hawkins, R., Daw, N., Cohen, J., Narasimhan, K., & Griffiths, T. (2022). Using natural language and program abstractions to instill human inductive biases in machines. In Proceedings of the 35th International Conference on Advances in Neural Information Processing Systems (NeurIPS'22).
- Kumar, S., Dasgupta, I., Cohen, J., Daw, N., & Griffiths, T. (2021). Meta-learning of structured task distributions in humans and machines. In *Proceedings of the Ninth* International Conference on Learning Representations (ICLR'21).
- Kwon, J., Efroni, Y., Caramanis, C., & Mannor, S. (2021). Rl for latent mdps: Regret guarantees and a lower bound.. In Ranzato et al. (Ranzato et al., 2021).
- Lampinen, A., Roy, N., Dasgupta, I., Chan, S., Tam, A., Mcclelland, J., Yan, C., Santoro, A., Rabinowitz, N., J. Wang, J., & Hill, F. (2022). Tell me why! explanations support learning relational and causal structure.. In Chaudhuri et al. (Chaudhuri et al., 2022).
- Lan, C., & Agarwal, R. (2023). Revisiting bisimulation: A sampling-based state similarity pseudo-metric. In *The First Tiny Papers Track at ICLR 2023, Tiny Papers @ ICLR 2023, Kigali, Rwanda, May 5, 2023.*
- Lan, C., Bellemare, M., & Castro, P. (2021). Metrics and continuity in reinforcement learning. In Yang et al. (Yang et al., 2021).
- Lan, Q., Mahmood, A., Yan, S., & Xu, Z. (2023). Learning to optimize for reinforcement learning. *CoRR*, *abs/2302.01470*.
- Lang, J. (Ed.). (2018). Proceedings of the 27th International Joint Conference on Artificial Intelligence (IJCAI'18).
- Laroche, R., & Feraud, R. (2022). Reinforcement learning algorithm selection. In *Proceedings* of the Sixth International Conference on Learning Representations (ICLR'22).
- Larochelle, H., Ranzato, M., Hadsell, R., Balcan, M.-F., & Lin, H. (Eds.). (2020). Proceedings of the 33rd International Conference on Advances in Neural Information Processing Systems (NeurIPS'20). Curran Associates.
- Laskin, M., Yarats, D., Liu, H., Lee, K., Zhan, A., Lu, K., Cang, C., Pinto, L., & Abbeel, P. (2021). URLB: unsupervised reinforcement learning benchmark. In Vanschoren, J., & Yeung, S. (Eds.), Proceedings of the Neural Information Processing Systems Track on Datasets and Benchmarks 1, NeurIPS Datasets and Benchmarks 2021, December 2021, virtual.
- Lee, A., Nagabandi, A., Abbeel, P., & Levine, S. (2020a). Stochastic latent actor-critic: Deep reinforcement learning with a latent variable model.. In Larochelle et al. (Larochelle et al., 2020).

- Lee, J., Hwangbo, J., Wellhausen, L., Koltun, V., & Hutter, M. (2020b). Learning quadrupedal locomotion over challenging terrain. *Science in Robotics*, 5.
- Lee, J., Sedwards, S., & Czarnecki, K. (2022). Recursive constraints to prevent instability in constrained reinforcement learning. In arXiv preprint arXiv:2201.07958.
- Lee, S., & Chung, S. (2021). Improving generalization in meta-rl with imaginary tasks from latent dynamics mixture.. In Ranzato et al. (Ranzato et al., 2021).
- Li, A., Spyra, O., Perel, S., Dalibard, V., Jaderberg, M., Gu, C., Budden, D., Harley, T., & Gupta, P. (2019). A generalized framework for population based training. In Teredesai, A., Kumar, V., Li, Y., Rosales, R., Terzi, E., & Karypis, G. (Eds.), Proceedings of the 25th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining (KDD'19), p. 1791–1799. ACM Press.
- Li, L., Walsh, T., & Littman, M. (2006). Towards a unified theory of state abstraction for mdps.. In  $AI\mathcal{E}M$ .
- Li, T., Pan, J., Zhu, D., & Meng, M. (2018). Learning to interrupt: A hierarchical deep reinforcement learning framework for efficient exploration. In 2018 IEEE International Conference on Robotics and Biomimetics (ROBIO), pp. 648–653. IEEE.
- Li, Y., Wu, Y., Xu, H., Wang, X., & Wu, Y. (2021). Solving compositional reinforcement learning problems via task reduction. In *Proceedings of the Ninth International Conference on Learning Representations (ICLR'21)*.
- Liao, L., Fu, Z., Yang, Z., Wang, Y., Kolar, M., & Wang, Z. (2021). Instrumental variable value iteration for causal offline reinforcement learning. *CoRR*, *abs/2102.09907*.
- Lipton, Z. (2018). The mythos of model interpretability. Commun. ACM, 61(10), 36–43.
- Lu, C., Kuba, J., Letcher, A., Metz, L., de Witt, C., & Foerster, J. (2022). Discovered policy optimisation. In neurips22.
- Lu, K., Zhang, S., Stone, P., & Chen, X. (2018). Robot representation and reasoning with knowledge from reinforcement learning. *CoRR*, *abs/1809.11074*.
- Lu, M., Shahn, Z., Sow, D., Doshi-Velez, F., & Lehman, L. H. (2020). Is deep reinforcement learning ready for practical applications in healthcare? A sensitivity analysis of duelddqn for hemodynamic management in sepsis patients. In AMIA 2020, American Medical Informatics Association Annual Symposium, Virtual Event, USA, November 14-18, 2020. AMIA.
- Luis, J., Miao, Y., Co-Reyes, J., Parisi, A., Tan, J., Real, E., & Faust, A. (2022). Multi-objective evolution for generalizable policy gradient algorithms. *CoRR*, *abs/2204.04292*.
- Lyu, D., Yang, F., Liu, B., & Gustafson, S. (2019). Sdrl: Interpretable and data-efficient deep reinforcement learning leveraging symbolic planning. In Hentenryck, P. V., & Zhou, Z. (Eds.), *Proceedings of the Thirty-Third Conference on Artificial Intelligence (AAAI'19)*. AAAI Press.
- lyu, Y., Côme, A., Zhang, Y., & Talebi, M. (2023). Scaling up q-learning via exploiting state-action equivalence. *Entropy*, 25(4), 584.

- Mahadevan, S., & Maggioni, M. (2007). Proto-value functions: A laplacian framework for learning representation and control in markov decision processes. *J. Mach. Learn. Res.*, 8, 2169–2231.
- Mahajan, A., Samvelyan, M., Mao, L., Makoviychuk, V., Garg, A., Kossaifi, J., Whiteson, S., Zhu, Y., & Anandkumar, A. (2021). Reinforcement learning in factored action spaces using tensor decompositions. In arXiv preprint arXiv:2110.14538.
- Mahajan, A., & Tulabandhula, T. (2017). Symmetry learning for function approximation in reinforcement learning. In arXiv preprint arXiv:1706.02999.
- Mambelli, D., Träuble, F., Bauer, S., Schölkopf, B., & Locatello, F. (2022). Compositional multi-object reinforcement learning with linear relation networks. In arXiv preprint arXiv:2201.13388.
- Mankowitz, D., Mann, T., & Mannor, S. (2015). Bootstrapping skills. In arXiv preprint arXiv:1506.03624.
- Mannor, S., & Tamar, A. (2023). Towards deployable rl-what's broken with rl research and a potential fix. In arXiv preprint arXiv:2301.01320.
- Martinez, D., Alenya, G., & Torras, C. (2017). Relational reinforcement learning with guided demonstrations. *Artificial Intelligence*, 247, 295–312.
- Marzi, T., Khehra, A., Cini, A., & Alippi, C. (2023). Feudal graph reinforcement learning. CoRR, abs/2304.05099.
- Mausam, D., & Weld, D. (2003). Solving relational mdps with first-order machine learning. In *Proceedings of the ICAPS workshop on planning under uncertainty and incomplete information.*
- Meila, M., & Zhang, T. (Eds.). (2021). Proceedings of the 38th International Conference on Machine Learning (ICML'21), Vol. 139 of Proceedings of Machine Learning Research. PMLR.
- Mendez, J., Hussing, M., Gummadi, M., & Eaton, E. (2022a). Composuite: A compositional reinforcement learning benchmark. In Chandar, S., Pascanu, R., & Precup, D. (Eds.), *Proceedings of the First Conference on Lifelong Learning Agents (CoLLAs'22)*, Vol. 199, pp. 982–1003. PMLR.
- Mendez, J., van Seijen, H., & Eaton, E. (2022b). Modular lifelong reinforcement learning via neural composition. In *Proceedings of the Tenth International Conference on Learning Representations (ICLR'22)*.
- Mendez, J., Wang, B., & Eaton, E. (2020). Lifelong policy gradient learning of factored policies for faster training without forgetting.. In Larochelle et al. (Larochelle et al., 2020).
- Meng, T., & Khushi, M. (2019). Reinforcement learning in financial markets. *Data*, 4(3), 110.
- Metz, L., Ibarz, J., Jaitly, N., & Davidson, J. (2017). Discrete sequential prediction of continuous actions for deep rl. In arXiv preprint arXiv:1705.05035.
- Mihajlovic, V., & Petkovic, M. (2001). Dynamic bayesian networks: A state of the art. In *University of Twente Document Repository*.

- Mirsky, R., Shperberg, S., Zhang, Y., Xu, Z., Jiang, Y., Cui, J., & Stone, P. (2022). Task factorization in curriculum learning. In *Decision Awareness in Reinforcement Learning Workshop at ICML 2022*.
- Misra, D., Henaff, M., Krishnamurthy, A., & Langford, J. (2020). Kinematic state abstraction and provably efficient rich-observation reinforcement learning. In III, & Singh (III & Singh, 2020).
- Modi, A., Jiang, N., Singh, S., & Tewari, A. (2018). Markov decision processes with continuous side information. In Janoos, F., Mohri, M., & Sridharan, K. (Eds.), Algorithmic Learning Theory, ALT 2018, 7-9 April 2018, Lanzarote, Canary Islands, Spain, Vol. 83 of Proceedings of Machine Learning Research, pp. 597–618. PMLR.
- Moerland, T., Broekens, J., Plaat, A., & Jonker, C. (2023). Model-based reinforcement learning: A survey. Found. Trends Mach. Learn., 16(1), 1–118.
- Mohamed, S., & Rezende, D. (2015). Variational information maximisation for intrinsically motivated reinforcement learning. In Cortes, C., Lawrence, N., Lee, D., Sugiyama, M., & Garnett, R. (Eds.), Proceedings of the 28th International Conference on Advances in Neural Information Processing Systems (NeurIPS'15). Curran Associates.
- Mohan, A., Benjamins, C., Wienecke, K., Dockhorn, A., & Lindauer, M. (2023). Autorl hyperparameter landscapes. In Faust, A., White, C., Hutter, F., Garnett, R., & Gardner, J. (Eds.), *Proceedings of the Second International Conference on Automated Machine Learning*. Proceedings of Machine Learning Research.
- Mu, J., Zhong, V., Raileanu, R., Jiang, M., Goodman, N., Rocktäschel, T., & Grefenstette, E. (2022a). Improving intrinsic exploration with language abstractions. In *Proceedings* of the 35th International Conference on Advances in Neural Information Processing Systems (NeurIPS'22).
- Mu, T., Lin, K., Niu, F., & Thattai, G. (2022b). Learning two-step hybrid policy for graph-based interpretable reinforcement learning. *Trans. Mach. Learn. Res.*, 2022.
- Mutti, M., Mancassola, M., & Restelli, M. (2022). Unsupervised reinforcement learning in multiple environments.. In Sycara et al. (Sycara et al., 2022).
- Mutti, M., Pratissoli, L., & Restelli, M. (2021). Task-agnostic exploration via policy gradient of a non-parametric state entropy estimate.. In Yang et al. (Yang et al., 2021).
- Nachum, O., Shane, S. G., Lee, H., & Levine, S. (2018). Data-efficient hierarchical reinforcement learning. In Bengio et al. (Bengio et al., 2018).
- Nam, T., Sun, S., Pertsch, K., Hwang, S. J., & Lim, J. (2022). Skill-based meta-reinforcement learning. In *Proceedings of the Tenth International Conference on Learning Representations (ICLR'22)*. OpenReview.net.
- Narvekar, S., Sinapov, J., Leonetti, M., & Stone, P. (2016). Source task creation for curriculum learning. In Jonker, C., Marsella, S., Thangarajah, J., & Tuyls, K. (Eds.), Proceedings of the International Conference on Autonomous Agents & Multiagent Systems (AAMAS'16), pp. 566–574. ACM.
- Ng, A., Harada, D., & Russell, S. (1999). Policy invariance under reward transformations: Theory and application to reward shaping. In Bratko, I. (Ed.), *Proceedings of the Six*-

- teenth International Conference on Machine Learning (ICML'99). Morgan Kaufmann Publishers.
- Oh, J., Hessel, M., Czarnecki, W., Xu, Z., van Hasselt, H., Singh, S., & Silver, D. (2020). Discovering reinforcement learning algorithms.. In Larochelle et al. (Larochelle et al., 2020).
- Ok, J., Proutière, A., & Tranos, D. (2018). Exploration in structured reinforcement learning.. In Bengio et al. (Bengio et al., 2018).
- Oliva, M., Banik, S., Josifovski, J., & Knoll, A. (2022). Graph neural networks for relational inductive bias in vision-based deep reinforcement learning of robot control. In *International Joint Conference on Neural Networks*, *IJCNN 2022*, *Padua*, *Italy*, *July 18-23*, 2022, pp. 1–9. IEEE.
- OpenAI (2023). GPT-4 technical report. CoRR, abs/2303.08774.
- Papini, M., Tirinzoni, A., Pacchiano, A., Restelli, M., Lazaric, A., & Pirotta, M. (2021). Reinforcement learning in linear mdps: Constant regret and representation selection.. In Ranzato et al. (Ranzato et al., 2021).
- Parker-Holder, J., Nguyen, V., & Roberts, S. J. (2020). Provably efficient online Hyperparameter Optimization with population-based bandits.. In Larochelle et al. (Larochelle et al., 2020).
- Parker-Holder, J., Rajan, R., Song, X., Biedenkapp, A., Miao, Y., Eimer, T., Zhang, B., Nguyen, V., Calandra, R., Faust, A., Hutter, F., & Lindauer, M. (2022). Automated reinforcement learning (AutoRL): A survey and open problems. *Journal of Artificial Intelligence Research (JAIR)*, 74, 517–568.
- Parr, R., & Russell, S. (1997). Reinforcement learning with hierarchies of machines. In Proceedings of the Tenth International Conference on Advances in Neural Information Processing Systems (NeurIPS'97).
- Pateria, S., Subagdja, B., Tan, A., & Quek, C. (2022). Hierarchical reinforcement learning: A comprehensive survey. *ACM Computing Surveys*, 54(5), 109:1–109:35.
- Pathak, D., Agrawal, P., Efros, A., & Darrell, T. (2017). Curiosity-driven exploration by self-supervised prediction. In Precup, & Teh (Precup & Teh, 2017).
- Pathak, D., Lu, C., Darrell, T., Isola, P., & Efros, A. (2019). Learning to control self-assembling morphologies: a study of generalization via modularity. In Wallach et al. (Wallach et al., 2019).
- Payani, A., & Fekri, F. (2020). Incorporating relational background knowledge into reinforcement learning via differentiable inductive logic programming. *CoRR*, *abs/2003.10386*.
- Peng, X., Chang, M., Zhang, G., Abbeel, P., & Levine, S. (2019). MCP: learning composable hierarchical control with multiplicative compositional policies.. In Wallach et al. (Wallach et al., 2019).
- Perez, C., Such, F., & Karaletsos, T. (2020). Generalized hidden parameter mdps transferable model-based rl in a handful of trials.. In Rossi et al. (Rossi et al., 2020).

- Peters, J., Buhlmann, P., & Meinshausen, N. (2016). Causal inference by using invariant prediction: identification and confidence intervals. *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, 78(5), 947–1012.
- Pitis, S., Creager, E., & Garg, A. (2020). Counterfactual data augmentation using locally factored dynamics.. In Larochelle et al., (Larochelle et al., 2020).
- Prakash, B., Waytowich, N., Ganesan, A., Oates, T., & Mohsenin, T. (2020). Guiding safe reinforcement learning policies using structured language constraints. In Espinoza, H., Hernández-Orallo, J., Chen, X. C., ÓhÉigeartaigh, S. S., Huang, X., Castillo-Effen, M., Mallah, R., & McDermid, J. A. (Eds.), Proceedings of the Workshop on Artificial Intelligence Safety, co-located with 34th AAAI Conference on Artificial Intelligence, SafeAI@AAAI 2020, New York City, NY, USA, February 7, 2020, Vol. 2560 of CEUR Workshop Proceedings, pp. 153–161. CEUR-WS.org.
- Prakash, B., Waytowich, N., Oates, T., & Mohsenin, T. (2022). Towards an interpretable hierarchical agent framework using semantic goals. *CoRR*, *abs/2210.08412*.
- Precup, D., & Teh, Y. (Eds.). (2017). Proceedings of the 34th International Conference on Machine Learning (ICML'17), Vol. 70. Proceedings of Machine Learning Research.
- Prudencio, R., Máximo, M., & Colombini, E. (2022). A survey on offline reinforcement learning: Taxonomy, review, and open problems. *CoRR*, *abs/2203.01387*.
- Puterman, M. (2014). Markov decision processes: discrete stochastic dynamic programming. John Wiley & Sons.
- Ranzato, M., Beygelzimer, A., Nguyen, K., Liang, P., Vaughan, J., & Dauphin, Y. (Eds.). (2021). Proceedings of the 34th International Conference on Advances in Neural Information Processing Systems (NeurIPS'21). Curran Associates.
- Raza, S., & Lin, M. (2019). Policy reuse in reinforcement learning for modular agents. In *IEEE 2nd International Conference on Information and Computer Technologies (ICICT)*. IEEE.
- Ross, S., & Pineau, J. (2008). Model-based bayesian reinforcement learning in large structured domains. In McAllester, D. A., & Myllymäki, P. (Eds.), *UAI 2008, Proceedings of the 24th Conference in Uncertainty in Artificial Intelligence, Helsinki, Finland, July 9-12, 2008*, pp. 476–483. AUAI Press.
- Rossi, F., Conitzer, V., & Sha, F. (Eds.). (2020). Proceedings of the Thirty-Fourth Conference on Artificial Intelligence (AAAI'20). Association for the Advancement of Artificial Intelligence, AAAI Press.
- Rusu, A., Colmenarejo, S., Gülçehre, C., Desjardins, G., Kirkpatrick, J., Pascanu, R., Mnih, V., Kavukcuoglu, K., & Hadsell, R. (2016). Policy distillation. In *Proceedings of Fourth International Conference on Learning Representations (ICLR'16)*.
- Salimans, T., Ho, J., Chen, X., & Sutskever, I. (2017). Evolution strategies as a scalable alternative to reinforcement learning. *CoRR*, *abs/1703.03864*.
- Sanner, S., & Boutilier, C. (2012). Approximate linear programming for first-order mdps. In arXiv preprint arXiv:1207.1415.

- Saxe, A., Earle, A., & Rosman, B. (2017). Hierarchy through composition with multitask lmdps.. In Precup, & Teh (Precup & Teh, 2017).
- Schaul, T., Horgan, D., Gregor, K., & Silver, D. (2015). Universal value function approximators. In Bach, F., & Blei, D. (Eds.), International conference on machine learning, Vol. 37. Omnipress.
- Schiewer, R., & Wiskott, L. (2021). Modular networks prevent catastrophic interference in model-based multi-task reinforcement learning. In *Proceedings of the Seventh International Conference on Machine Learning, Optimization, and Data Science (LOD'21)*, Vol. 13164 of *Lecture Notes in Computer Science*, pp. 299–313. Springer.
- Seitzer, M., Schölkopf, B., & Martius, G. (2021). Causal influence detection for improving efficiency in reinforcement learning. In Ranzato et al. (Ranzato et al., 2021).
- Shanahan, M., Nikiforou, K., Creswell, A., Kaplanis, C., Barrett, D., & Garnelo, M. (2020). An explicitly relational neural network architecture. In *icml20*.
- Sharma, A., Gu, S., Levine, S., Kumar, V., & Hausman, K. (2020). Dynamics-aware unsupervised discovery of skills. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR'20)*. OpenReview.net.
- Sharma, V., Arora, D., Geisser, F., Mausam, A., & Singla, P. (2022). Symnet 2.0: Effectively handling non-fluents and actions in generalized neural policies for rddl relational mdps. In *Uncertainty in Artificial Intelligence*, pp. 1771–1781. PMLR.
- Shu, T., Xiong, C., & Socher, R. (2018). Hierarchical and interpretable skill acquisition in multi-task reinforcement learning. In *Proceedings of the Sixth International Conference on Learning Representations (ICLR'18)*.
- Shyam, P., Jaskowski, W., & Gomez, F. (2019). Model-based active exploration.. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).
- Silver, D., Huang, A., Maddison, C., Guez, A., Sifre, L., Driessche, G., Schrittwieser, J., Antonoglou, I., Panneershelvam, V., Lanctot, M., Dieleman, S., Grewe, D., Nham, J., Kalchbrenner, N., Sutskever, I., Lillicrap, T., Leach, M., Kavukcuoglu, K., Graepel, T., & Hassabis, D. (2016). Mastering the game of go with deep neural networks and tree search. Nature, 529(7587), 484–489.
- Simao, T., Jansen, N., & Spaan, M. (2021). Alwayssafe: Reinforcement learning without safety constraint violations during training. In *Proceedings of the 20th International Conference on Autonomous Agents and MultiAgent Systems*.
- Singh, G., Peri, S. V., Kim, J., Kim, H., & Ahn, S. (2021). Structured world belief for reinforcement learning in POMDP.. In Meila, & Zhang (Meila & Zhang, 2021).
- Sodhani, S., Levine, S., & Zhang, A. (2022a). Improving generalization with approximate factored value functions. In *ICLR2022 Workshop on the Elements of Reasoning: Objects, Structure and Causality*.
- Sodhani, S., Meier, F., Pineau, J., & Zhang, A. (2022b). Block contextual mdps for continual learning. In *Learning for Dynamics and Control Conference*.
- Sodhani, S., Zhang, A., & Pineau, J. (2021). Multi-task reinforcement learning with context-based representations.. In Meila, & Zhang (Meila & Zhang, 2021).

- Sohn, S., Oh, J., & Lee, H. (2018). Hierarchical reinforcement learning for zero-shot generalization with subtask dependencies.. In Bengio et al. (Bengio et al., 2018).
- Sohn, S., Woo, H., Choi, J., & Lee, H. (2020). Meta reinforcement learning with autonomous inference of subtask dependencies. In *Proceedings of the Eighth International Conference on Learning Representations*, (ICLR'20). OpenReview.net.
- Solway, A., Diuk, C., Córdova, N., Yee, D., Barto, A., Niv, Y., & Botvinick, M. (2014). Optimal behavioral hierarchy. *PLoS Comput. Biol.*, 10(8).
- Song, Y., Suganthan, P., Pedrycz, W., Ou, J., He, Y., & Chen, Y. (2023). Ensemble reinforcement learning: A survey. *CoRR*, *abs/2303.02618*.
- Spooner, T., Vadori, N., & Ganesh, S. (2021). Factored policy gradients: Leveraging structure for efficient learning in momdps.. In Ranzato et al. (Ranzato et al., 2021).
- Srinivas, A., & Abbeel, P. (2021). Unsupervised Learning for Reinforcement Learning...
- Srouji, M., Zhang, J., & Salakhutdinov, R. (2018). Structured control nets for deep reinforcement learning.. In Dy, & Krause (Dy & Krause, 2018).
- Steccanella, L., Totaro, S., & Jonsson, A. (2021). Hierarchical representation learning for markov decision processes. In arXiv preprint arXiv:2106.01655.
- Sun, Y., Ma, S., Madaan, R., Bonatti, R., Huang, F., & Kapoor, A. (2023). SMART: self-supervised multi-task pretraining with control transformers. In *Proceedings of the Eleventh International Conference on Learning Representations (ICLR'23)*.
- Sun, Y., Yin, X., & Huang, F. (2021). Temple: Learning template of transitions for sample efficient multi-task rl.. In Yang et al. (Yang et al., 2021).
- Sutton, R. (1988). Learning to predict by the methods of temporal differences. *Mach. Learn.*, 3, 9–44.
- Sutton, R., McAllester, D., Singh, S., & Mansour, Y. (1999a). Policy gradient methods for reinforcement learning with function approximation. In Solla, S., Leen, T., & Müller, K. (Eds.), Proceedings of the 12th International Conference on Advances in Neural Information Processing Systems (NeurIPS'99). The MIT Press.
- Sutton, R., Precup, D., & Singh, S. (1999b). Between mdps and semi-mdps: A framework for temporal abstraction in reinforcement learning. *Artificial Intelligence*, 112(1-2), 181–211.
- Sutton, R. S., & Barto, A. G. (2018). Reinforcement learning: An introduction (2 edition). Adaptive computation and machine learning. MIT Press.
- Sycara, K., Honavar, V., & Spaan, M. (Eds.). (2022). Proceedings of the Thirty-Sixth Conference on Artificial Intelligence (AAAI'22). Association for the Advancement of Artificial Intelligence, AAAI Press.
- Talele, N., & Byl, K. (2019). Mesh-based tools to analyze deep reinforcement learning policies for underactuated biped locomotion. In arXiv preprint arXiv:1903.12311.
- Talvitie, E., & Singh, S. (2008). Simple local models for complex dynamical systems. In Proceedings of the 21st International Conference on Advances in Neural Information Processing Systems (NeurIPS'08).

- Tang, S., Makar, M., Sjoding, M., Doshi-Velez, F., & Wiens, J. (2022a). Leveraging factored action spaces for efficient offline reinforcement learning in healthcare. In *Decision Awareness in Reinforcement Learning Workshop at ICML 2022*.
- Tang, S., Makar, M., Sjoding, M., Doshi-Velez, F., & Wiens, J. (2022b). Leveraging factored action spaces for efficient offline reinforcement learning in healthcare. In *Decision Awareness in Reinforcement Learning Workshop at ICML 2022*.
- Tavakol, M., & Brefeld, U. (2014). Factored mdps for detecting topics of user sessions. In *Proceedings of the 8th ACM Conference on Recommender Systems*.
- Tavakoli, A., Pardo, F., & Kormushev, P. (2018). Action branching architectures for deep reinforcement learning. In McIlraith, S., & Weinberger, K. (Eds.), *Proceedings of the Thirty-Second Conference on Artificial Intelligence (AAAI'18)*. AAAI Press.
- Tennenholtz, G., & Mannor, S. (2019). The natural language of actions.. In Chaudhuri, & Salakhutdinov (Chaudhuri & Salakhutdinov, 2019).
- Trimponias, G., & Dietterich, T. (2023). Reinforcement learning with exogenous states and rewards. In arXiv preprint arXiv:2303.12957.
- Tsividis, P., Loula, J., Burga, J., Foss, N., Campero, A., Pouncy, T., Gershman, S., & Tenenbaum, J. (2021). Human-level reinforcement learning through theory-based modeling, exploration, and planning. *CoRR*, *abs/2107.12544*.
- van der Pol, E., Kipf, T., Oliehoek, F., & Welling, M. (2020). Plannable approximations to mdp homomorphisms: Equivariance under actions. In *Proceedings of the 19th International Conference on Autonomous Agents and Multiagent Systems*.
- van Rossum, C., Feinberg, C., Shumays, A. A., Baxter, K., & Bartha, B. (2021). A novel approach to curiosity and explainable reinforcement learning via interpretable sub-goals. *CoRR*, *abs/2104.06630*.
- Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need.. In Guyon et al. (Guyon et al., 2017).
- Veerapaneni, R., Co-Reyes, J., Chang, M., Janner, M., Finn, C., Wu, J., Tenenbaum, J., & Levine, S. (2020). Entity abstraction in visual model-based reinforcement learning. In *Conference on Robot Learning*. PMLR.
- Verma, A., Murali, V., Singh, R., Kohli, P., & Chaudhuri, S. (2018). Programmatically interpretable reinforcement learning. In *icml18*.
- Wallach, H., Larochelle, H., Beygelzimer, A., d'Alche Buc, F., Fox, E., & Garnett, R. (Eds.). (2019). Proceedings of the 32nd International Conference on Advances in Neural Information Processing Systems (NeurIPS'19). Curran Associates.
- Wan, X., Lu, C., Parker-Holder, J., Ball, P., Nguyen, V., Ru, B., & Osborne, M. (2022). Bayesian generational population-based training. In Guyon, I., Lindauer, M., van der Schaar, M., Hutter, F., & Garnett, R. (Eds.), Proceedings of the First International Conference on Automated Machine Learning. Proceedings of Machine Learning Research.
- Wang, G., Fang, Z., Li, B., & Li, P. (2016). Integrating symmetry of environment by designing special basis functions for value function approximation in reinforcement

- learning. In Fourteenth International Conference on Control, Automation, Robotics and Vision.
- Wang, H., Dong, S., & Shao, L. (2019). Measuring structural similarities in finite mdps.. In Kraus, S. (Ed.), Proceedings of the 28th International Joint Conference on Artificial Intelligence (IJCAI'19).
- Wang, J., King, M., Porcel, N., Kurth-Nelson, Z., Zhu, T., Deck, C., Choy, P., Cassin, M., Reynolds, M., Song, H., Buttimore, G., Reichert, D., Rabinowitz, N., Matthey, L., Hassabis, D., Lerchner, A., & Botvinick, M. (2021). Alchemy: A benchmark and analysis toolkit for meta-reinforcement learning agents.. In Ranzato et al. (Ranzato et al., 2021).
- Wang, J., Liu, Y., & Li, B. (2020). Reinforcement learning with perturbed rewards.. In Rossi et al. (Rossi et al., 2020).
- Wang, Q., & van Hoof, H. (2022). Model-based meta reinforcement learning using graph structured surrogate models and amortized policy search.. In Chaudhuri et al. (Chaudhuri et al., 2022).
- Wang, T., Du, S., Torralba, A., Isola, P., Zhang, A., & Tian, Y. (2022). Denoised mdps: Learning world models better than the world itself. In arXiv preprint arXiv:2206.15477.
- Wang, T., Liao, R., Ba, J., & Fidler, S. (2018). Nervenet: Learning structured policy with graph neural networks. In *Proceedings of the Sixth International Conference on Learning Representations (ICLR'18)*.
- Wang, T., Torralba, A., Isola, P., & Zhang, A. (2023). Optimal goal-reaching reinforcement learning via quasimetric learning. *CoRR*, *abs/2304.01203*.
- Wen, Z., Precup, D., Ibrahimi, M., Barreto, A., Roy, B. V., & Singh, S. (2020). On efficiency in hierarchical reinforcement learning. In Larochelle et al. (Larochelle et al., 2020).
- Whatley, A., Luo, Z., & Tang, X. (2021). Improving RNA secondary structure design using deep reinforcement learning. *CoRR*, *abs/2111.04504*.
- Whitehead, S., & Lin, L. (1995). Reinforcement learning of non-markov decision processes. *Artif. Intell.*, 73(1-2), 271–306.
- Williams, R. (1992a). Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Mach. Learn.*, 8, 229–256.
- Williams, R. (1992b). Simple statistical gradient-following algorithms for connectionist reinforcement learning. *Mach. Learn.*, 8, 229–256.
- Wolf, L., & Musolesi, M. (2023). Augmented modular reinforcement learning based on heterogeneous knowledge. *CoRR*, *abs/2306.01158*.
- Woo, H., Yoo, G., & Yoo, M. (2022). Structure learning-based task decomposition for reinforcement learning in non-stationary environments.. In Sycara et al. (Sycara et al., 2022).
- Wu, B., Gupta, J., & Kochenderfer, M. (2019). Model primitive hierarchical lifelong reinforcement learning. In Elkind, E., Veloso, M., Agmon, N., & Taylor, M. (Eds.), Proceedings of the Eighteenth International Conference on Autonomous Agents and

- MultiAgent Systems (AAMAS'19), pp. 34–42. International Foundation for Autonomous Agents and Multiagent Systems.
- Wu, C., Rajeswaran, A., Duan, Y., Kumar, V., Bayen, A., Kakade, S., Mordatch, I., & Abbeel, P. (2018). Variance reduction for policy gradient with action-dependent factorized baselines. In *Proceedings of the Sixth International Conference on Learning Representations (ICLR'18)*.
- Xu, D., & Fekri, F. (2021). Interpretable model-based hierarchical reinforcement learning using inductive logic programming. *CoRR*, *abs/2106.11417*.
- Xu, K., Verma, S., Finn, C., & Levine, S. (2020). Continual learning of control primitives: Skill discovery via reset-games. In Larochelle et al. (Larochelle et al., 2020).
- Yang, C., Hung, I., Ouyang, Y., & Chen, P. (2022). Training a resilient q-network against observational interference.. In Sycara et al. (Sycara et al., 2022).
- Yang, F., Lyu, D., Liu, B., & Gustafson, S. (2018). Peorl: Integrating symbolic planning and hierarchical reinforcement learning for robust decision-making.. In Lang (Lang, 2018).
- Yang, Q., Leyton-Brown, K., & Mausam (Eds.). (2021). Proceedings of the Thirty-Fifth Conference on Artificial Intelligence (AAAI'21). Association for the Advancement of Artificial Intelligence, AAAI Press.
- Yang, R., Xu, H., Wu, Y., & Wang, X. (2020a). Multi-task reinforcement learning with soft modularization.. In Larochelle et al. (Larochelle et al., 2020).
- Yang, Y., Zhang, G., Xu, Z., & Katabi, D. (2020b). Harnessing structures for value-based planning and reinforcement learning. In *Proceedings of the Eighth International Conference on Learning Representations (ICLR'20)*. OpenReview.net.
- Yarats, D., Fergus, R., Lazaric, A., & Pinto, L. (2021). Reinforcement learning with prototypical representations. In Meila, M., & Zhang, T. (Eds.), *icml21*.
- Yin, D., Thiagarajan, S., Lazic, N., Rajaraman, N., Hao, B., & Szepesvári, C. (2023). Sample efficient deep reinforcement learning via local planning. *CoRR*, *abs/2301.12579*.
- Young, K., Ramesh, A., Kirsch, L., & Schmidhuber, J. (2022). The benefits of model-based generalization in reinforcement learning. In arXiv preprint arXiv:2211.02222.
- Yu, D., Ma, H., Li, S., & Chen, J. (2022). Reachability constrained reinforcement learning. In Chaudhuri et al. (Chaudhuri et al., 2022).
- Zambaldi, V., Raposo, D., Santoro, A., Bapst, V., Li, Y., Babuschkin, I., Tuyls, K., Reichert,
  D., Lillicrap, T., Lockhart, E., Shanahan, M., Langston, V., Pascanu, R., Botvinick,
  M., Vinyals, O., & Battaglia, P. (2019). Deep reinforcement learning with relational inductive biases. In Proceedings of the Seventh International Conference on Learning Representations, ICLR 2019. OpenReview.net.
- Zeng, K., Zhang, Q., Chen, B., Liang, B., & Yang, J. (2022). APD: learning diverse behaviors for reinforcement learning through unsupervised active pre-training. *IEEE Robotics Autom. Lett.*, 7(4), 12251–12258.
- Zhang, A., Lyle, C., Sodhani, S., Filos, A., Kwiatkowska, M., Pineau, J., Gal, Y., & Precup, D. (2020). Invariant causal prediction for block mdps.. In III, & Singh (III & Singh, 2020).

- Zhang, A., McAllister, R., Calandra, R., Gal, Y., & Levine, S. (2021). Learning invariant representations for reinforcement learning without reconstruction. In *Proceedings of the Ninth International Conference on Learning Representations (ICLR'21)*.
- Zhang, A., Sodhani, S., Khetarpal, K., & Pineau, J. (2020). Multi-task reinforcement learning as a hidden-parameter block mdp. In arXiv preprint arXiv:2007.07206.
- Zhang, A., Sodhani, S., Khetarpal, K., & Pineau, J. (2021a). Learning robust state abstractions for hidden-parameter block mdps. In *Proceedings of the Ninth International Conference on Learning Representations (ICLR'21)*.
- Zhang, C., Cai, Y., Huang, L., & Li, J. (2021b). Exploration by maximizing renyi entropy for reward-free RL framework.. In Yang et al. (Yang et al., 2021).
- Zhang, D., Courville, A., Bengio, Y., Zheng, Q., Zhang, A., & Chen, R. (2022). Latent state marginalization as a low-cost approach for improving exploration. *CoRR*, *abs/2210.00999*.
- Zhang, H., Chen, H., Xiao, C., Li, B., Liu, M., Boning, D., & Hsieh, C. (2020). Robust deep reinforcement learning against adversarial perturbations on state observations.. In Larochelle et al. (Larochelle et al., 2020).
- Zhang, H., Gao, Z., Zhou, Y., Zhang, H., Wu, K., & Lin, F. (2019a). Faster and safer training by embedding high-level knowledge into deep reinforcement learning. *CoRR*, *abs/1910.09986*.
- Zhang, H., Gao, Z., Zhou, Y., Zhang, H., Wu, K., & Lin, F. (2019b). Faster and safer training by embedding high-level knowledge into deep reinforcement learning. *CoRR*, *abs/1910.09986*.
- Zhang, S., Tong, H., Xu, J., & Maciejewski, R. (2019c). Graph convolutional networks: a comprehensive review. *Computational Social Networks*, 6(1), 1–23.
- Zhang, X., & Yu, S. Z. Y. (2021). Domain knowledge guided offline q learning. In Second Offline Reinforcement Learning Workshop at Neurips 2021.
- Zhao, T., Xie, K., & Eskénazi, M. (2019). Rethinking action spaces for reinforcement learning in end-to-end dialog agents with latent variable models. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*.
- Zhou, A., Kumar, V., Finn, C., & Rajeswaran, A. (2022). Policy architectures for compositional generalization in control. In arXiv preprint arXiv:2203.05960.
- Zhou, Z., Li, X., & Zare, R. (2017). Optimizing chemical reactions with deep reinforcement learning. ACS central science, 3(12), 1337–1344.
- Zhu, J., Park, T., Isola, P., & Efros, A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision*, pp. 2223–2232.