CONSTRUCTING A GOOD BEHAVIOR BASIS FOR TRANSFER USING GENERALIZED POLICY UPDATES

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ABSTRACT

We study the problem of learning a good set of policies, so that when combined together, they can solve a wide variety of unseen reinforcement learning tasks with no or very little new data. Specifically, we consider the framework of generalized policy evaluation and improvement, in which the rewards for all tasks of interest are assumed to be expressible as a linear combination of a fixed set of features. We show theoretically that, under certain assumptions, having access to a specific set of diverse policies, which we call a set of independent policies, can allow for instantaneously achieving high-level performance on all possible downstream tasks, although these tasks are typically more complex than the ones on which the agent was trained. Based on this theoretical analysis, we propose a simple algorithm that iteratively constructs this set of policies. In addition to empirically validating our theoretical results, we compare our approach with recently proposed diverse policy set construction methods and show that, while others fail, our approach is able to build a behavior basis that enables instantaneous transfer to all possible downstream tasks. We also show empirically that having access to a set of independent policies can better bootstrap the learning process on downstream tasks where the new reward function cannot be described as a linear combination of the features. Finally, we demonstrate that this policy set can be useful in a realistic lifelong reinforcement learning setting.

1 INTRODUCTION

Reinforcement learning (RL) studies the problem of building rational decision-making agents that maximize long term cumulative reward through trial-and-error interaction with a given environment. In recent years, RL algorithms combined with powerful function approximators such as deep neural networks have achieved significant successes in a wide range of challenging domains, see e.g. Mnih et al. (2015); Vinyals et al. (2019); Silver et al. (2017; 2018). However, these algorithms require substantial amounts of data for performing very narrowly-defined tasks. In addition to being data-hungry, they are also very brittle to changes in the environment, such as changes in the tasks over time.

A promising approach to tackle both of these shortcomings is to learn multiple ways of behaving, i.e., multiple policies that optimize different reward functions, and to reuse them as needed. Having access to multiple previously-learned policies can allow an agent to quickly solve reoccurring tasks in a lifelong RL setting. It can also allow for learning to combine the existing policies via a meta-policy to quickly learn new tasks, as in hierarchical RL. Recently, Barreto et al. (2020) have proposed the "generalized policy updates" framework, which generalizes the classical policy evaluation and policy improvement operations that underlie many of today's RL algorithms. Its goal is to allow reusing policies resulting from previously learned tasks in order to perform well on downstream tasks, while also being data-efficient. More precisely, they learn policies for different tasks, and corresponding successor features, which model the expected value of discounted cumulative feature vectors encountered when executing these policies. Using this information, they were able to instantaneously "synthesize", in a zero-shot manner, new policies to solve related downstream tasks, via generalized policy improvement. However, this work leaves open two important questions: (1) what set of policies should the agent learn so that its instantaneous performance on *all* possible downstream tasks is guaranteed to be good, and (2) under what conditions does such a set of policies exist.

In this paper, we provide answers to the questions above by proving that under certain assumptions about the environment dynamics and features, learning a diverse set of policies, which we call a *set of independent policies*, indeed guarantees good instantaneous performance on all possible downstream tasks. We provide an iterative algorithm for the construction of this set, and we perform several experiments using this algorithm. The results validate our theoretical findings. In addition to these validation experiments, we compare this algorithm with recently proposed diverse policy set construction methods (Eysenbach et al., 2018; Zahavy et al., 2020; 2021) and show that, unlike these methods, our approach is able to construct a behavior basis that enables instantaneous transfer to all possible tasks. We also show empirically that learning a set of independent policies can better bootstrap the learning process on downstream tasks where the reward function cannot be described by a single linear combination of the features. Finally, we demonstrate the usefulness of this set in a realistic lifelong RL scenario, in which the agent faces different tasks over its lifetime. We hope that our study will bring the community a step closer to building lifelong RL agents that are able to perform multiple tasks and a to instantaneously/quickly adapt to new ones.

2 Background

Reinforcement Learning. In RL (Sutton & Barto, 2018), an agent interacts with its environment by choosing actions to get as much as cumulative long-term reward. The interaction between the agent and its environment is usually modeled as a Markov Decision Process (MDP). An MDP is a tuple $M \equiv (\mathcal{S}, \mathcal{A}, P, r, d_0, \gamma)$, where $\mathcal{S}$ is the (finite) set of states, $\mathcal{A}$ is the (finite) set of actions, $P : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to [0, 1]$ is the transition distribution, $r : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \to \mathbb{R}$ is the reward function, which specifies the task of interest, $d_0 : \mathcal{S} \to [0, 1]$ is the initial state distribution and $\gamma \in [0, 1)$ is the discount factor. In RL, typically the agent does not have any knowledge about P and r beforehand, and its goal is to find, through pure interaction, a policy $\pi : \mathcal{S} \to \mathcal{A}$ that maximizes the expected sum of discounted rewards $E_{\pi,P}[\sum_{t=0}^{\infty} \gamma^t r(S_t, A_t, S_{t+1}) | S_0 \sim d_0]$, where $E_{\pi,P}[\cdot]$ denotes the expectation over trajectories induced by π and P.

Successor Features. The successor representation for a state s under a policy π allows s to be represented by the (discounted) distribution of states encountered when following π from s (Dayan, 1993). Given a policy, successor features (SF, Barreto et al., 2017) are a generalization of the idea of successor representations from the tabular setting to function approximation. Following Barreto et al. (2017), we define SFs of a policy π for state-action (s, a) as:

$$\boldsymbol{\psi}^{\pi}(s, a) \equiv E_{\pi,P}\left[\sum_{i=0}^{\infty} \gamma^i \boldsymbol{\phi}(S_{t+i}, A_{t+i}, S_{t+i+1}) \middle| S_t = s, A_t = a\right], \tag{1}$$

where the ith component of $\boldsymbol{\psi}^{\pi}$ gives the expected discounted sum of the ith component of the feature vector, ϕ_i, when following policy π, starting from the state-action pair (s, a).

Successor features allow a decoupling between the reward function and the environment dynamics. More concretely, if the reward function for a task can be represented as a linear combination of a feature vector $\boldsymbol{\phi}(s, a, s') \in \mathbb{R}^n$:

$$r_{\mathbf{w}}(s, a, s') = \boldsymbol{\phi}(s, a, s')^{\top} \cdot \mathbf{w}, \tag{2}$$

where $\mathbf{w} \in \mathbb{R}^n$, then the state-action value function $Q^{\pi}_{r_{\mathbf{w}}}$ can be computed immediately as the dot-product of $\boldsymbol{\psi}^{\pi}$ and $\mathbf{w}$. The elements of $\mathbf{w}$, w_i, can be viewed as indicating a "preference" towards each of the features. Thus, we refer to $\mathbf{w}$ interchangeably as either the preference vector or the task. Intuitively, the elements ϕ_i of the feature vector $\boldsymbol{\phi}$ can be viewed as salient events that maybe desirable or undesirable to the agent, such as picking up or leaving objects of certain type, and reaching and/or avoiding certain states.

Generalized Policy Evaluation and Improvement. Generalized Policy Evaluation (GPE) and Generalized Policy Improvement (GPI), together referred to as Generalized Policy Updates, are generalizations of the well-known policy evaluation and policy improvement operations in standard dynamic programming to a set of tasks and a set of policies (Barreto et al., 2020). They are used as a transfer mechanism in RL to quickly construct a solution for a newly given task. One particularly efficient instantiation of GPE & GPI is through the use of SFs and value-based action selection. More concretely, given a set of MDPs having the following form:

$$\mathcal{M}_{\phi} \equiv \{(\mathcal{S}, \mathcal{A}, P, r_{\mathbf{w}} = \boldsymbol{\phi} \cdot \mathbf{w}, d_0, \gamma) | \mathbf{w} \in \mathbb{R}^n\}, \tag{3}$$

and given SFs $\boldsymbol{\psi}^{\pi}(s,a)$ of a policy π, an efficient form of GPE on the task $r_{\mathbf{w}}$ for policy π can be performed as follows:

$$\boldsymbol{\psi}^{\pi}(s,a)^{\top} \cdot \mathbf{w} = Q^{\pi}_{r_{\mathbf{w}}}(s,a), \tag{4}$$

where $Q^{\pi}_{r_{\mathbf{w}}}(s,a)$ is the state-action value function of π on the task $r_{\mathbf{w}}$. And, after performing GPE for all the policies π in a finite policy set Π, following Barreto et al. (2017), an efficient form of GPI can be performed as follows:

$$\pi^{\text{GPI}}_{\Pi}(s) \in \arg\max_{a\in\mathcal{A}} \max_{\pi\in\Pi} Q^{\pi}_{r_{\mathbf{w}}}(s,a). \tag{5}$$

We will refer to this specific use of SFs and value-based action selection for performing GPE & GPI as simply GPE & GPI throughout the rest of this study. Note that π^{GPI} will in general outperform all the policies in Π, and that the actions selected by π^{GPI} on a state may not coincide with any of the actions selected by $\pi \in \Pi$ on that state. Hence, the policy space that can be attained by GPI can in principle be a lot larger than, e.g., the space accessible by calling sequentially policies from the original set.

3 Problem Formulation and Theoretical Analysis

GPE & GPI provide a guarantee that, for any reward function linear in the features, π^{GPI} is at least as good as any of the policies π from the "base set" which was used to construct it. While this is an appealing guarantee of monotonic improvement, it does not say much, for two reasons. First, it is not clear how big an improvement can be expected for different tasks. More importantly, it leave open the question of how one should choose base policies in order to ensure as much improvement as possible. After all, if we had a weak set of policies and we simply matched their value with π^{GPI}, this may not be very useful. We will now show that, under certain assumptions, having access to a specific set of diverse policies, which we call a set of independent policies, can allow instantaneously achieving high-level performance on *all* possible downstream tasks.

Let us start by assuming that we are interested in a set of MDPs $\mathcal{M}_{\phi}$, as defined in (3), with deterministic transition functions (the reason for the determinism assumption will become clear by the end this section). For convenience, we also restrict the possible $\mathbf{w}$ values from $\mathbb{R}^n$ to $\mathcal{W}$, where $\mathcal{W}$ is the surface of the ℓ_2 n-dimensional ball. Note that this choice does not alter the optimal policies of the MDPs in $\mathcal{M}_{\phi}$, as an optimal policy is invariant with respect to the scale of the reward and $\mathcal{W}$ contains all possible directions. Next, we assume that the features ϕ_i that make up the feature vectors $\boldsymbol{\phi}$ form a *set of independent features*, defined as follows:

Definition 1 (Set of Independent Features)**.** *A set features $\Phi = \{\phi_i | \phi_i : \mathcal{S}\times\mathcal{A}\times\mathcal{S} \to \{0, C\}, C \in \mathbb{R}_+\}_{i=1}^{n}$ is called* independent *if, for any feature $\phi_i \in \Phi$ and any initial state $s_0 \sim d_0$, we have: (1) $\phi_i(s_0, a_0, s_1) = 0$, where $a_0 = \pi(s_0)$ and (2) there exists at least one trajectory, starting from s_0, in which all the states associated with $\phi_i(s_t, a_t, s_{t+1}) = C$ are visited, while the states associated with $\phi_j(s_t, a_t, s_{t+1}) = C$, for all $j \neq i$, are not visited.*

It should be noted that a specific instantiation of this definition is the case where each feature is set to a positive constant at certain independently reachable state/states and zero elsewhere, which is the most common instantiation of feature vectors used in previous related work (Barreto et al., 2017; 2020).

We define the performance of an arbitrary policy π on a task $r_{\mathbf{w}}$ as:

$$J^{\pi}_{r_{\mathbf{w}}} \equiv E_{\pi,d_0}\left[Q^{\pi}_{r_{\mathbf{w}},\gamma=1}(S,A)\right], \tag{6}$$

where $Q^{\pi}_{r_{\mathbf{w}},\gamma=1}$ is the undiscounted state-action value function of policy π on task $r_{\mathbf{w}}$. Note that $J^{\pi}_{r_{\mathbf{w}}}$ is a scalar corresponding to the expected undiscounted return of policy π under the initial state distribution d_0, which is the expected total reward obtained by π when starting from $s_0 \sim d_0$. We are now ready to formalize the problem wee want to tackle.

Problem Formulation. Given a set of MDPs $\mathcal{M}_{\phi}$ with deterministic transition functions and a set of independent features, we want to construct a set of n policies $\Pi^n = \{\pi_i\}_{i=1}^{n}$, such that the performance of the policy $\pi^{\text{GPI}}_{\Pi^n}$ obtained by performing GPI starting from that set will maximize (6) for all rewards $r_{\mathbf{w}}$, where $\mathbf{w} \in \mathcal{W}$. That is, we want to solve the following problem:

$$\arg\max_{\Pi^n \subseteq \Pi} J^{\pi^{\text{GPI}}_{\Pi^n}}_{r_{\mathbf{w}}} \text{ for all } \mathbf{w} \in \mathcal{W}. \tag{7}$$

It should be noted that the performance measure provided in (6) only measures the expected total reward and thus cannot capture the optimality of the GPI policy. For instance, this measure cannot distinguish between two policies that achieve the same expected total reward in a different number of time steps. However, Theorem 2 in Barreto et al. (2017) implies that, in general, the only way to guarantee the optimality of the GPI policy is to construct a behavior basis that contains all possible policies induced by all $\mathbf{w} \in \mathcal{W}$. Since there are infinitely many $\mathbf{w}$ values, this is impractical. Thus, in this study, we only consider GPI policies that maximize the expected total reward (6).

As a solution candidate to the problem in (7), we now focus on a specific set of deterministic policies, called *set of independent policies*, that are able to obtain features independently of each other:

Definition 2 (Set of Independent Policies)**.** *Let $\Phi = \{\phi_i\}_{i=1}^n$ be a set of independent features and let $\Pi = \{\pi_i\}_{i=1}^n$ be a set of deterministic policies that are induced by each of the features in Φ. Π is defined to be a* set of independent policies *if its elements, π_i, satisfy:*

$$\phi_j(s_t, a_t, s_{t+1}) = \phi_j(s_0, a_0, s_1)\ \forall j \neq i,\ \forall i,\ \forall s_0 \sim d_0 \text{ and } \forall t \in \{1, \dots, T\}, \tag{8}$$

where T is the horizon in episodic environments and $T \to \infty$ in non-episodic ones, $a_0 = \pi_i(s_0)$ and $(s_t, a_t, s_{t+1})_{t=1}^T$ is the sequence of state-action-state triples generated by π_i's interaction with the environment.

In general, having a set of independent policies in a set of MDPs with stochastic transition functions is not possible, as the stochasticity can prevent (8) from holding. Thus, the assumption of a set of MDPs with deterministic transition functions is critical to our analysis. An immediate consequence of having this set of policies is that the corresponding SFs can be expressed in a simpler form, as follows:

Lemma 1. *Let ϕ_j be a member of a set of independent features Φ and let π_i be a policy that is induced by feature ϕ_i and is a member of a set of independent policies Π. Then, the entries of the SF $\boldsymbol{\psi}^{\pi_i}$ of policy π_i has the following form:*

$$\psi_j^{\pi_i}(s, a) = \begin{cases} \dfrac{1}{1-\gamma}\phi_j(s, a), & \text{if } j \neq i \\ \psi_i^{\pi_i}(s, a), & \text{otherwise} \end{cases}, \tag{9}$$

where $\phi_j(s, a) = E_P[\phi_j(S, A, S')|S = s, A = a]$.

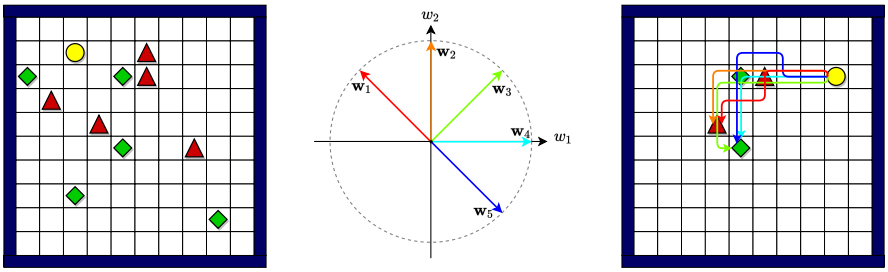
Due to the space constraints, we provide all the proofs in the supplementary material. Lemma 1 implies that once we have a set of independent policies, the SFs take the much simpler form (1), which can allow for the GPI policy to maximize performance on *all* possible tasks according to the measure in (6), solving the optimization objective (7):

Theorem 1. *Let Φ be a set of independent features and let Π be a set of independent policies induced by each of the features in Φ. Then, the GPI policy π_Π^{GPI} is a solution to the optimization problem defined in (7).*

Theorem 1 implies that having access to a set of independent policies which consists of only n policies, where n is the dimensionality of $\boldsymbol{\phi}$, and applying the policy composition operator GPI on top, allows for instantaneously achieving maximum performance across all possible downstream tasks. Considering the fact that there are *infinitely many* such tasks, this provides a significant gain in the number of tasks that need to be solved.

4 Constructing a Set of Independent Policies

Based on our theoretical analysis in Section 3, we now propose a simple algorithm that iteratively constructs a set of independent policies, given a set of independent features. Since independent policies can attain certain features without affecting the others, a set can be constructed by simply learning policies for each of the appropriate tasks and then by adding these learned policies one-by-one to an initially empty set. In particular, by sequentially learning policies for each of the tasks in $W = \{\mathbf{w}_i\}_{i=1}^n \subset \mathcal{W}$, where $\mathbf{w}_i$ is an n-dimensional vector with a positive number in the ith coordinate and negative numbers elsewhere, and the adding these policies to a policy set, one can construct a set of independent policies. Algorithm 1 provides a step-by-step description of this



(a) Environment (b) Preference vectors (c) Trajectories

Figure 1: (a) The 2D item collection environment (Barreto et al., 2020). The environment consists of 10×10 cells and the shape (traingle and diamond) of the items represents their type. (b) Five distinct preference vectors that lie on the surface of the ℓ_2 2-dimensional ball: $\mathbf{w}_1 = (-\sqrt{1/2} \; +\sqrt{1/2})$, $\mathbf{w}_2 = (0 \; +1)$, $\mathbf{w}_3 = (+\sqrt{1/2} \; +\sqrt{1/2})$, $\mathbf{w}_4 = (+1 \; 0)$ and $\mathbf{w}_5 = (+\sqrt{1/2} \; -\sqrt{1/2})$. (c) The trajectories taken by the optimal policies ($\gamma = 0.95$) corresponding to the preference vectors $\mathbf{w}_1, \ldots, \mathbf{w}_5$ in a simplified version of the environment with two items of each type.

construction process. Note that the algorithm does not depend on the particular values of $\mathbf{w}_i \in W$ as long as the corresponding coordinate has a positive value and all others are negative. Another thing to note is that the algorithm runs for only n iterations, where n is the dimensionality of the feature vector $\boldsymbol{\phi}$.

5 Experiments

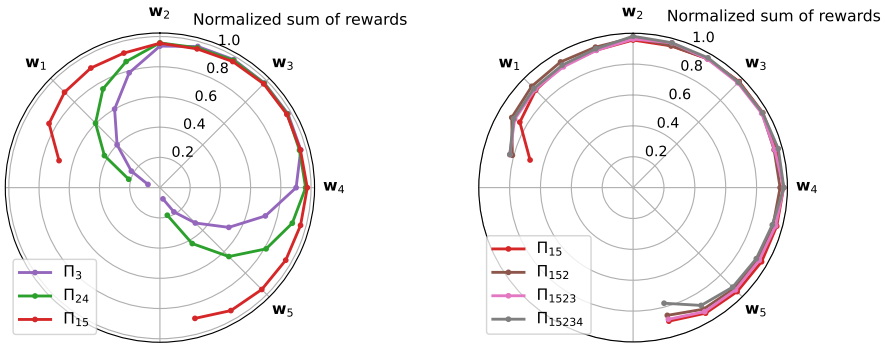
We start this section by performing experiments to illustrate the theoretical results derived in Section 3. Then, we compare the performance of the policy construction approach presented in Algorithm 1 with recently proposed diverse policy set construction methods (Eysenbach et al., 2018; Zahavy et al., 2020; 2021). Next, we show that a set of independent policies can better bootstrap learning on new tasks where the reward function cannot in fact be expressed as a linear combination of the features, a case that lies outside of our assumptions. Finally, we demonstrate that the set of policies produced by our approach can be useful in a realistic lifelong RL setting. The experimental details together with more detailed results can be found in the supplementary material.

Algorithm 1: Constructing a Set of Independent Policies

Initialize: $\Pi^0 \leftarrow \{\}$, $t \leftarrow 1$, $W \leftarrow \{\mathbf{w}_i\}_{i=1}^n$;
while $t \leq n$ **do**
  $\mathbf{w}_t \leftarrow W[t]$;
  $\pi^t \leftarrow$ solution of the task $r_{\mathbf{w}_t}$ using RL ;
  $\Pi^t \leftarrow \Pi^{t-1} + \{\pi^t\}$;
  $t \leftarrow t + 1$;
end
return: Π^n

Experimental Setup. Throughout this section, we perform experiments on the 2D item collection environment proposed in Barreto et al. (2020) (see Fig. 1a), as it is a prototypical environment where GPE & GPI is useful and it allows for easy visualization of performance across all downstream tasks. Here, the agent, depicted by the yellow circle, starts randomly in one of the cells and has to obtain/avoid 5 randomly placed red and green items, which are of different type. At each time step, the agent receives an image that contains its own position and the position and type of each item. Based on this, the agent selects an action that deterministically moves it to one of its four neighboring cells. By moving to the cells occupied by an item, the agent picks up that item and gets a reward defined by that item type. The goal of the agent is to pick up the "good" items and avoid the "bad" ones, depending on the preference vector $\mathbf{w}$. The agent-environment interaction lasts for 50 time steps, after which the agent receives a "done" signal, marking the end of the episode. Note that despite its small size, the cardinality of this environment's state space is on the order of 10^{15} and thus requires the use of function approximation. More details on the environment can be found in Barreto et al. (2020).

In order to use GPE & GPI in this environment, we must first define: (1) the features $\boldsymbol{\phi}$ and (2) a set of policies Π. Following Barreto et al. (2020), we define each feature ϕ_i as an indicator function signalling whether an item of type i has been picked up by the agent. That is, $\phi_i(s, a, s') = 1$ if taking action a in state s results in picking up an item of type i, and $\phi_i(s, a, s') = 0$ otherwise. Note



(a) Disjoint sets

(b) Incrementally growing sets

Figure 2: The normalized sum of rewards over 17 evenly spread tasks over the nonnegative quadrants of the unit circle. The plots are obtained by averaging over 10 runs with 1000 episodes for each task. The performance comparison of Π_{15} (a) with disjoint sets Π_{24} and Π_5, and (b) with incrementally growing sets Π_{152}, Π_{1523} and Π_{15234}.

that these form a set of independent features, as there exist trajectories which start as $\phi(s_0, a_0, s_1) = 0$ and in which all the features associated with a certain item type can be obtained without affecting the others. We now turn to the question on how to determine the set of policies Π. We restrict the policies in Π to be solutions of the tasks $\mathbf{w} \in \mathcal{W}$. With Algorithm 1, we have already provided one way of constructing this set. Throughout the rest of this section we will compare Algorithm 1 with alternative ways of obtaining policies.

Following Barreto et al. (2020), we use an algorithm analogous to Q-learning to approximate the SFs induced by ϕ and Π. Similarly, we represent the SFs using multilayer perceptrons with two hidden layers. More details can be found in Barreto et al. (2020).

5.1 Illustrative Experiments

Question 1. *Does the theoretical results, derived in Section 3, also hold empirically?*

In order to answer this question, we constructed a policy set using Algorithm 1 and evaluated it using the evaluation scheme proposed by Barreto et al. (2020). Specifically, after initializing $W = \{\mathbf{w}_1, \mathbf{w}_5\}$ and running Algorithm 1, we obtained the independent policy set $\Pi_{15} = \{\pi_1, \pi_5\}$, whose elements are solutions to the tasks $\mathbf{w}_1$ and $\mathbf{w}_5$, respectively (see Fig. 1b). Then, we ran an evaluation scheme that evaluates the GPI policy $\pi^{\text{GPI}}_{\Pi_{15}}$, over 17 evenly spread tasks over the nonnegative quadrants of the unit circle in Fig. 1b. We did not perform evaluation in the negative quadrant, as the tasks there are not interesting. Results are shown in Fig. 2a. As can be seen, $\pi^{\text{GPI}}_{\Pi_{15}}$ performs well across all the downstream tasks, as expected based on the result in Theorem 1.

Question 2. *Is having a set of independent policies essential for full downstream task coverage?*

According to Theorem 1, having a set of independent policies is a requirement for guaranteeing good performance across all downstream tasks. However, in order to see how well the GPI policy performs when this is not the case, similar to Barreto et al. (2020), we compared Π_{15} with two other possible policy sets: $\Pi_{24} = \{\pi_2, \pi_4\}$ and $\Pi_3 = \{\pi_3\}$, whose policies correspond to the tasks $\mathbf{w}_2$, $\mathbf{w}_4$ and $\mathbf{w}_3$, respectively. It should be noted that Π_{24} is a default policy set used in prior studies on SFs (Barreto et al., 2017; 2018; 2020; Borsa et al., 2018). The results, in Fig. 2a, show that $\pi^{\text{GPI}}_{\Pi_{24}}$ and $\pi^{\text{GPI}}_{\Pi_3}$ are not able to perform well across all downstream tasks, specifically failing on quadrants II and IV. This justifies the requirement of learning a set of independent policies for full downstream task coverage.

Question 3. *Do the SFs of the policies in a set of independent policies have a simple form?*

According to Lemma 1, the SFs of the policies in a set of independent policies should have a simple form. To empirically verify this, in Fig. 3, we visualize the SFs of the policies in the sets Π_{15} and Π_{24} for the simplified environment depicted in Fig. 1c. We can see that the SFs of the policies in

Π_{15} indeed have a simple form, in which the off-diagonal entries have values that are very close to zero; this is not the case for Π_{24}.

Question 4. *Does adding more policies to a set of independent policies have any effect on its downstream task coverage?*

Theorem 1 implies that having a set of independent policies is enough to guarantee good performance across all possible tasks. To test empirically whether adding more policies to the set has any effect on the performance across all tasks, we compare the performance of the policy set Π_{15} with policy sets Π_{152}, Π_{1523} and Π_{15234}, formed by adding one-by-one the policies π_2, π_3 and π_4 to Π_{15}. Results are shown in Fig. 2b. As expected, adding more policies to the set of independent policies Π_{15} has no effect on downstream task performance.

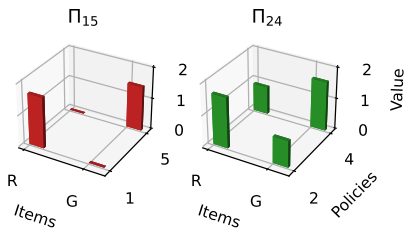


Figure 3: The learned SFs of the policies in Π_{15} and Π_{24} for the state in Fig. 1c and the left action. Here, each row corresponds to a different policy and each column corresponds to a different item ('R'ed and 'G'reen).

5.2 Comparative and Lifelong Learning Experiments

Question 5. *How does Algorithm 1 compare to prior diverse policy set construction methods?*

Prior work has shown that having access to a diverse set of policies can help transfer to downstream tasks. Algorithm 1 can also be seen as a diverse policy set construction method, as it constructs a policy set that is diverse in the feature visitation profile. In order to see how well it compares to prior work, we compare Algorithm 1 with three recently proposed diverse policy set construction methods: (1) DIAYN[1] (Eysenbach et al., 2018) which constructs a policy set by collectively training policies with information-theoretic reward functions that encourage discriminablity among the policies in the set based on their state visitation profile, (2) SMP (Zahavy et al., 2020) which constructs a policy set by iteratively adding policies trained on the worst-case linear reward with respect to the previous policies in the set, and (3) DSP (Zahavy et al., 2021) which constructs a policy set by iteratively adding policies that are trained on tasks $\mathbf{w}_n = -(1/n)\sum_{k=0}^{n}\boldsymbol{\psi}_k$, where n is the number of policies in the current policy set. More on the specific implementation details of these methods can be found in the supplementary material. The comparison results, shown in Fig. 4, indicate that none of the prior diverse policy set construction methods are able to consistently construct a policy set that enables full downstream task coverage.

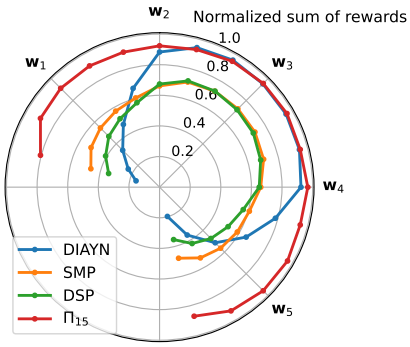


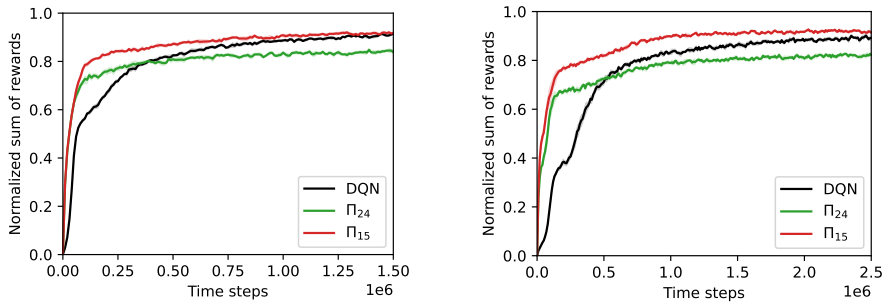
Figure 4: The normalized sum of rewards of Π_{15}, and the policy sets constructed by DIAYN, SMP and DSP. Since the policy sets constructed by the prior methods depend on their particular initialization, their plots are obtained by running each of the constructed policy sets for 5 runs and then averaging over their results. For each task, the agent was evaluated on 1000 episodes. The plot for Π_{15} is obtained in a similar way as in Fig. 2.

Question 6. *Is learning a set of independent policies also effective when the downstream task's reward function is not a single linear combination of the features?*

So far, we have considered the scenario where the GPI policy is evaluated on tasks whose reward functions were obtained by linearly combining the features $\boldsymbol{\phi}$ using a single, fixed $\mathbf{w}$. We now consider downstream tasks that do now satisfy this assumption, e.g. where $\mathbf{w}$ changes as a function over the environment's state. Theorem 1 has nothing to say in this case. Nevertheless, in order to test whether if learning a set of independent policies can still be useful in this scenario, we consider a transfer setting in which a meta-policy is trained to orchestrate the policies in this set when faced

[1] We have used a GPE & GPI compatible version of DIAYN whose details are provided in the supp. material.

with a downstream task. Specifically, after constructing the policy set, we learn a function that maps states to preference vectors, $\omega : \mathcal{S} \rightarrow \mathcal{W}'$, whose output is then used by GPE & GPI synthesize a policy for the downstream task of interest (see the "Preferences as Actions" section in Barreto et al. (2020) and the Option Keyboard framework (Barreto et al., 2019) for more details). We define $\mathcal{W}' = \{\mathbf{w}_1, \mathbf{w}_2, \mathbf{w}_3, \mathbf{w}_4, \mathbf{w}_5\}$ and use Q-learning to learn ω.



(a) Sequential reward collection task

(b) Balanced reward collection task

Figure 5: The normalized sum of rewards of the policy sets Π_{15} and Π_{24}, and DQN on the (a) sequential reward collection and (b) balanced reward collection tasks. Shadowed regions are one standard error over 10 runs.

As an instantiation of the scenario discussed above, we consider two different downstream tasks, depicted in Fig. 1a: (1) sequential reward collection, in which the agent must first pick up items of a certain type and then collect the items of the other type, and (2) balanced reward collection, in which the agent must pick up the type of item that is more abundant in the environment. We compared the performance of the set of independent policies Π_{15} with the policy set Π_{24}. As a reference to the maximum reachable performance, we also provided the learning curve of DQN (Mnih et al., 2015), whose specific implementation details can be found in the supplementary material. The results, shown in Fig. 5a and 5b, show that Π_{15} outperforms Π_{24} both in terms of the learning speed and asymptotic performance, reaching the asymptotic performance of DQN. These results suggest that having access to a set of independent policies can also be effective in scenarios where the downstream task's reward function cannot be described as a single linear combination of the features.

Question 7. *How can learning a set of independent policies be useful in a lifelong RL setting?*

Except for the last question, we have considered an idealistic scenario in which, during transfer, the agent was provided with a single preference vector $\mathbf{w}$ describing a stationary downstream task of interest. We now consider a lifelong RL setting, in which the agent has to infer the current $\mathbf{w}$ from data and has to quickly adapt to the changing $\mathbf{w}$'s during its lifetime. Concretely, we consider the setting in which the agent infers $\mathbf{w}$ by following the regression procedure provided in Barreto et al. (2020) and the tasks change from $\mathbf{w}_1$ to $\mathbf{w}_5$ one-by-one in a clockwise fashion every 5×10^5 time steps. After the end of task $\mathbf{w}_5$, the task resets back to $\mathbf{w}_1$ and this task cycle goes on forever.

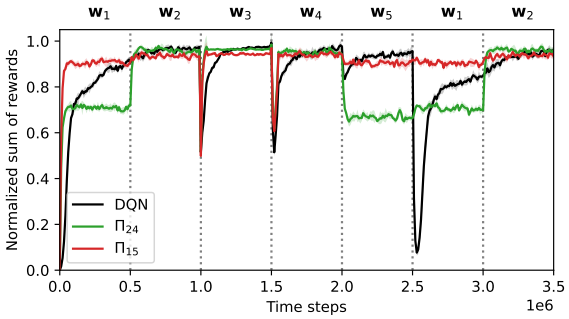


Figure 6: The normalized sum of rewards of the policy sets Π_{15} and Π_{24}, and DQN in a lifelong RL setting described in the text. Shadowed regions are one standard error over 100 runs.

In Fig. 6, we compare the performance of Π_{15} with the policy set Π_{24} and with DQN. We see that the policy set Π_{15} allows for better transfer to changing tasks compared to Π_{24}. We also see that DQN fails in transferring useful knowledge between changing task, sometimes catastrophically failing on tasks that it has already encountered before (see the drastic drop in performance when the

task transitions from $\mathbf{w}_5$ to $\mathbf{w}_1$). These results illustrate how a set of independent policies can also be useful in a realistic lifelong RL scenario.

6 Related Work

Successor Features & Generalized Policy Improvement. In this study, we focused on relevant work that uses a set of SFs together with GPI for performing transfer in RL. These studies start with the seminal work of Barreto et al. (2017) and continue with Barreto et al. (2018; 2019; 2020); Borsa et al. (2018); Hansen et al. (2019). Among them, the study of Barreto et al. (2020) is the closest to our work. We built on top of their approach and tried to answer the following questions: (1) what behavior basis should be learned by the agent so that its instantaneous performance on all possible downstream tasks is guaranteed to be good, and (2) what are the conditions required for this? In addition, we provided empirical results illustrating how a good behavior basis can be useful in realistic scenarios. Another closely related work is the study of Grimm et al. (2019) which shows that having access to a set of policies that obtain certain disentangled features can allow for achieving high level performance on exponentially many downstream goal-reaching tasks. However, this study requires having access to disentangled features, which have a very specific form; in contrast, we require a set of independent features, which are more general and commonly used (Barreto et al., 2017; 2020). Additionally, we provide a more formal treatment of the instantaneous transfer problem and our experiments address a broader range of questions.

Diverse Skill Discovery with Information Theory. Another related line of research is the information theoretic diverse skill discovery literature (Gregor et al., 2016; Eysenbach et al., 2018; Achiam et al., 2018), in which information theoretic objectives are used to construct a diverse policy set that enables better exploration and transfer when used in downstream tasks. One problem with learning these diverse set of skills is that most of the discovered policies end up being uninteresting, in the sense that they do not come to be useful in solving downstream tasks of interest, filling up the set with not so interesting policies. Our work prevents this by constructing a policy set in which every policy is trained to achieve only a particular task so that when combined can solve more complex downstream tasks of interest. A second important problem with these approaches is that they provide no instantaneous policy composition operators as GPI and thus come with no theoretical guarantees on the downstream task coverage. In contrast, we build on top of the GPE & GPI framework which enables for deriving theoretical guarantees.

Diverse Skill Discovery with Successor Features. Other related literature includes the use of SFs to build a diverse skill set either to guarantee good performance on the worst-case downstream task or to achieve a single downstream task in multiple different ways (Zahavy et al., 2020; 2021). Through using the formal criterion of robustness, Zahavy et al. (2020) proposes a method that constructs a set of policies that do as well as possible in the worst-case scenario and shows that this set naturally becomes diverse. However, a problem with this policy construction method is that it is sensitive to the initialization of the preference vector and thus leads to policy sets that do not have full downstream task coverage. By using explicit diversity rewards, Zahavy et al. (2021) proposes another method that aims to minimize the correlation between the SFs of the policies in the constructed set. However, since this method depends on the evolution of the policy set, it also fails in building a policy set with full downstream tasks coverage; by contrast, Algorithm 1 does exactly this.

7 Conclusion and Future Work

To summarize, in this study, we provided a theoretical analysis elucidating what counts as a good behavior basis for performing GPE & GPI and showed that, under certain assumptions, having access to a set of independent policies allows for instantaneously achieving high level performance on all tasks. We proposed a simple algorithm that iteratively constructs this policy set. Our empirical results illustrate our theoretical results, show that the proposed algorithm compares favourably to prior methods, and demonstrate that a set of independent policies can be useful in lifelong RL. Note that our approach relies on the existence of an independent set of features, which are maximized to obtain independent policies. In general, an orthogonalization procedure may be needed as a preprocessing step to obtain such features. We also hope to find useful generalizations of these ideas to the stochastic case.

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A PROOFS

Lemma 1. *Let ϕ_j be a member of a set of independent features Φ and let π_i be a policy that is induced by feature ϕ_i and is a member of a set of independent policies Π. Then, the entries of the SF $\boldsymbol{\psi}^{\pi_i}$ of policy π_i has the following form:*

$$\psi_j^{\pi_i}(s,a) = \begin{cases} \dfrac{1}{1-\gamma}\phi_j(s,a), & \text{if } j \neq i \\ \psi_i^{\pi_i}(s,a), & \text{otherwise} \end{cases},$$

where $\phi_j(s,a) = E_P[\phi_j(S,A,S')|S=s, A=a]$.

Proof. The proof follows directly from the definition of a set of independent policies. Remember that for a policy π_i that is a member of a set of independent policies, we have that:

$$\phi_j(s_t,a_t,s_{t+1}) = \phi_j(s_0,a_0,s_1)\ \forall j \neq i, \forall i, \forall s_0 \sim d_0 \text{ and } \forall t \in \{1,\dots,T\},$$

where T is the horizon, $a_0 = \pi_i(s_0)$ and $(s_t,a_t,s_{t+1})_{t=1}^T$ is the sequence of state-action-state triples that are generated by π_i's interaction with the environment. Thus, for $j \neq i$, we have:

$$\begin{aligned}
\psi_j^{\pi_i}(s,a) &= E_{\pi_i,P}\left[\sum_{k=0}^{\infty}\gamma^k\phi_j(S_{t+k},A_{t+k},S_{t+k+1})\Big|S_t=s,A_t=a\right] \\
&= E_P\left[\sum_{k=0}^{\infty}\gamma^k\phi_j(S_t,A_t,S_{t+1})\Big|S_t=s,A_t=a\right] && \text{(by Definition 2)} \\
&= \sum_{k=0}^{\infty}\gamma^k E_P[\phi_j(S_t,A_t,S_{t+1})|S_t=s,A_t=a] \\
&= \sum_{k=0}^{\infty}\gamma^k\phi_j(s,a) \\
&= \frac{1}{1-\gamma}\phi_j(s,a).
\end{aligned}$$

□

Theorem 1. *Let Φ be a set of independent features and let Π be a set of independent policies induced by each of the features in Φ. Then, the GPI policy π_Π^{GPI} is a solution to the optimization problem defined in (7).*

Proof. Remember that the GPI policy for a downstream task $\mathbf{w}$ is obtained as:

$$\pi_\Pi^{\text{GPI}}(s) \in \arg\max_{a\in\mathcal{A}} Q_{r_\mathbf{w}}^{\max}(s,a),$$

where $Q_{r_\mathbf{w}}^{\max}(s,a) = \max_{\pi_i\in\Pi} Q_{r_\mathbf{w}}^{\pi_i}(s,a)$. By expressing $Q_{r_\mathbf{w}}^{\pi_i}(s,a)$ as a weighted sum of the SFs of policy π_i, we have:

$$\begin{aligned}
Q_{r_\mathbf{w}}^{\max}(s,a) &= \max_i\left[\sum_{j=1}^{n} w_j\psi_j^{\pi_i}(s,a)\right] \\
&= \max_i\left[w_i\psi_i^{\pi_i}(s,a) + \sum_{j\neq i} w_j\psi_j^{\pi_i}(s,a)\right] \\
&= \max_i\left[w_i\psi_i^{\pi_i}(s,a) + \frac{1}{1-\gamma}\sum_{j\neq i} w_j\phi_j(s,a)\right] && \text{(by Lemma 1)} \\
&= \max_i\left[w_i\psi_i^{\pi_i}(s,a) + \frac{1}{1-\gamma}\sum_{j\neq i} w_j\phi_j(s_0,a_0)\right] && \text{(by Definition 2)}
\end{aligned}$$

$$= \max_i \left[w_i \psi_i^{\pi_i}(s,a) \right]. \qquad \text{(by Definition 1)}$$

Thus, we have:

$$\pi_{\Pi}^{\text{GPI}}(s) \in \arg\max_{a \in \mathcal{A}} Q_{r_{\mathbf{w}}}^{\max}(s,a)$$
$$= \arg\max_{a \in \mathcal{A}} \max_i \left[w_i \psi_i^{\pi_i}(s,a) \right],$$

which implies that the GPI policy π_{Π}^{GPI} will obtain all the features associated with a positive w_i (in an order that depends on the product $w_i \psi_i^{\pi_i}(s,a)$), ignore the ones with a zero w_i, and avoid the ones with a negative w_i. This in turn implies that the GPI policy π_{Π}^{GPI} will solve the problem in (7). □

B Experimental Details

In this section, we provide the experimental details of our policy construction method together with the prior methods that we have used for comparison.

B.1 Our Method and DQN

For our experiments with GPE & GPI and DQN (Mnih et al., 2015), we have used the publicly available code[2] of Barreto et al. (2020). Thus, implementation details as the neural network architectures that are used, the hyperparameters (replay buffer sizes, learning rates etc.) and the way the SFs and state-action value functions are learned can all be found both in the provided link and in the supplementary material of Barreto et al. (2020). We have also followed the same experimental protocol provided in the supplementary material of Barreto et al. (2020).

B.2 Prior Diverse Policy Set Construction Methods

Before moving on to the implementation details of the prior diverse policy set construction methods, we start this section by defining the concept of *reward equivalent policies*. This definition allows for a simple representation of the policy sets that are constructed by these prior methods in terms of the policy sets that can be induced by the nine preference vectors in Fig. 7.

Definition 3 (Reward Equivalent Policies)**.** *Let π_i and π_j be two policies that are induced by tasks $\mathbf{w}_i$ and $\mathbf{w}_j$, respectively. π_i and π_j are defined to be reward equivalent if they achieve the same expected total reward, i.e. if:*

$$E_{\pi_i, d_0}\left[Q_{r_{\mathbf{w}}, \gamma=1}^{\pi_i}(S,A) \right] = E_{\pi_j, d_0}\left[Q_{r_{\mathbf{w}}, \gamma=1}^{\pi_j}(S,A) \right].$$

It should be noted that even if two policies are induced by two different tasks, they can still be reward equivalent. For instance, the policies induced by the tasks $(0.6\ 0.8)$ and $(0.8\ 0.6)$ are reward equivalent as they achieve the same expected total reward by collecting all the items in the environment depicted in Fig. 1a. Note that Definition 3 only takes into account what the policies achieve and not how they exactly achieve it.

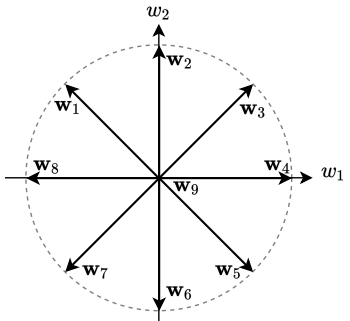


Figure 7: Eight different preference vectors that lie on the surface of the ℓ_2 2-dimensional ball and a single preference vector ($\mathbf{w}_9$) that is at the origin of this ball. The corresponding values are: $\mathbf{w}_1 = (-\sqrt{1/2}\ +\sqrt{1/2})$, $\mathbf{w}_2 = (0\ +1)$, $\mathbf{w}_3 = (+\sqrt{1/2}\ +\sqrt{1/2})$, $\mathbf{w}_4 = (+1\ 0)$, $\mathbf{w}_5 = (+\sqrt{1/2}\ -\sqrt{1/2})$, $\mathbf{w}_6 = (0\ -1)$ $\mathbf{w}_7 = (-\sqrt{1/2}\ -\sqrt{1/2})$, $\mathbf{w}_8 = (-1\ 0)$, $\mathbf{w}_9 = (0\ 0)$.

Importantly, Definition 3 allows for defining equivalences between policy sets. For instance, the policy set induced by tasks $(0.6\ 0.8)$ and $(0.6\ -0.8)$ contains a policy that collects both of the items (reward equivalent to π_3) and a policy that collects the first item while avoiding the second one

[2] https://github.com/deepmind/deepmind-research/tree/master/option_keyboard

(reward equivalent to π_5). The policy set Π_{35} also contains policies that achieve the same tasks. Thus, the former policy set can be considered to be reward equivalent to the policy set Π_{35}. Note that another policy set induced by tasks $(0.8\ 0.6)$ and $(0.8\ -0.6)$ can also be considered to be reward equivalent to the policy set Π_{35}. In the rest of this section, we will use this reward equivalence relation for a simple representation of the policy sets constructed by prior methods (in terms of the policy sets that can be induced by the preference vectors in Fig. 7).

DIAYN (Eysenbach et al., 2018). Among the prior diverse policy set construction methods that we have used, all except DIAYN are compatible with the GPE & GPI framework. Thus, in order to also make DIAYN compatible, while discovering a set of diverse policies, we have concurrently learned the SFs of the policies in this set so that GPE & GPI can be performed later on. Importantly, rather than encouraging diversity in the state visitation profile, we have encouraged diversity in the *feature visitation profile* by feeding the visited feature vectors $\boldsymbol{\phi}$ as input to the discriminator (as opposed to feeding the visited states as in regular DIAYN). This is because we are interested in policies that are able to obtain certain features, as opposed to ones that just push the agent to different parts of the state space. For the RL algorithm, we have used a vanilla policy gradient algorithm with an additional entropy loss term, for preventing the policy from becoming deterministic in the early stages of training.

After setting the number of policies to be discovered to 3 (as there are 3 possible feature vectors in the environment depicted in Fig. 1a: $(1\ 0)$, $(0\ 1)$ and $(0\ 0)$), learning the SFs of these policies and running the GPE & GPI compatible version of DIAYN described above, we have observed that the discovered policies either end up being policies that obtain both of the items (reward equivalent to π_3) or policies that obtain none (reward equivalent to π_7), corresponding to a policy set that is reward equivalent to the policy set Π_{37} (see Fig. 7). Thus, the results presented in Fig. 4 corresponds to the results obtained with the policy set Π_{37}. We have also experimented with larger numbers of policies to be discovered, however, we observed no difference in the qualitative behavior of the policies that were discovered.

In our experiments, for the representation of the policy we have used the same neural network architecture that was provided in Barreto et al. (2020). The hyperparameters of our implementation are provided in Table 1.

Table 1: Hyperparameters of our DIAYN implementation.

Learning rate of the policy	$1e-3$
Learning rate of the discriminator	$1e-3$
Discount	0.95
Entropy coefficient	0.001
Gradient clip	1.00
Value function loss coefficient	0.05

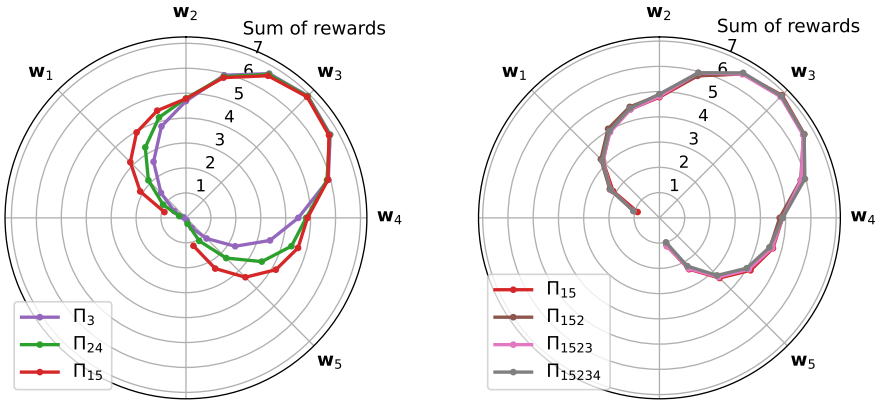
SMP (Zahavy et al., 2020). After initializing the preference vector to an arbitrary vector on the surface of the ℓ_2 2-dimensional ball (see Fig. 7) and running the SMP algorithm till termination, we have observed that for each initialization of preference vector, different policy sets were constructed. The resulting policy sets end up being reward equivalent to one of the following sets: Π_{37}, Π_{17}, Π_{157}, Π_{57}, Π_{517}, Π_{27}, Π_{47}, Π_{7}, Π_{87}, Π_{857}, Π_{8517}, Π_{617}, Π_{6157} and Π_{67}. Thus, the results presented in Fig. 4 correspond to the average results obtained by these policy sets.

DSP (Zahavy et al., 2021). After initializing the preference vector to an arbitrary vector on the surface of the ℓ_2 2-dimensional ball (see Fig. 7), setting $T = 2$ (see Algorithm 1 in Zahavy et al. (2021) for the details) and running the DSP algorithm, we have observed that for each initialization of preference vector, different policy sets were constructed. The resulting policy sets end up being reward equivalent to one of the following sets: Π_{37}, Π_{58}, Π_{16}, Π_{27}, Π_{47}, Π_{79}, Π_{68} and Π_{86}. Thus, the results presented in Fig. 4 correspond to the average results obtained by these policy sets.

We have also experimented with larger T values, however, after $T = 2$ the only policy to be added to the set is a policy that is reward equivalent to π_7. For instance, when $T = 3$, the resulting policy sets end up being reward equivalent to one of the following sets: Π_{377}, Π_{587}, Π_{167}, Π_{277}, Π_{477}, Π_{797} and Π_{867}. Since π_7 is a policy that avoids the items in the environment depicted in Fig. 1a, it is not a useful policy for the tasks considered in this study. Thus, we reported results only for the case of $T = 2$.

C UNNORMALIZED RESULTS

In this section, we provide the unnormalized results for the experiments in Section 5. The r- and y-axis of the plots now indicates the sum of rewards as it is, without any normalization.



(a) Disjoint sets

(b) Incrementally growing sets

Figure 8: The unnormalized sum of rewards over 17 evenly spread tasks over the nonnegative quadrants of the unit circle. The plots are obtained by averaging over 10 runs with 1000 episodes for each task. The performance comparison of (a) Π_{15} with disjoint sets Π_{24} and Π_5, and (b) Π_{15} with incrementally growing sets Π_{152}, Π_{1523} and Π_{15234}.

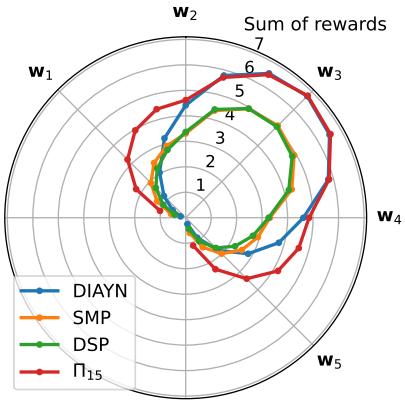
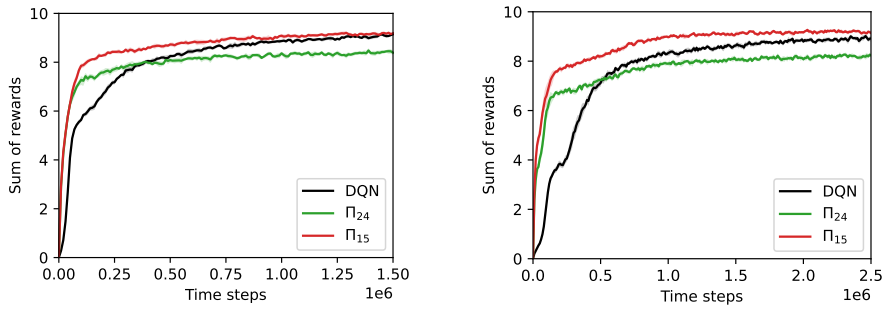


Figure 9: The unnormalized sum of rewards of Π_{15}, and the policy sets constructed by DIAYN, SMP and DSP. Since the policy sets constructed by the prior methods depend on their particular initialization, their plots are obtained by running each of the constructed policy sets for 5 runs and then averaging over their results. For each task, the agent was evaluated on 1000 episodes. The plot for Π_{15} is obtained in a similar way as in Fig. 8.



(a) Sequential reward collection task

(b) Balanced reward collection task

Figure 10: The unnormalized sum of rewards of the policy sets Π_{15} and Π_{24}, and DQN on the (a) sequential reward collection and (b) balanced reward collection tasks. Shadowed regions are one standard error over 10 runs.

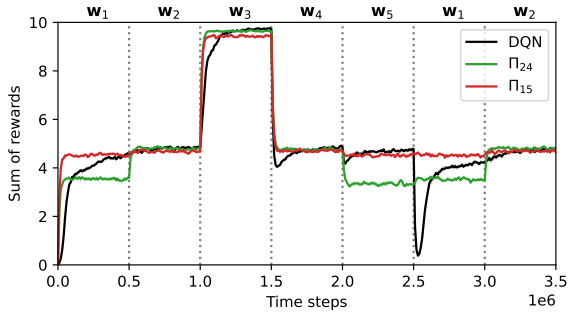


Figure 11: The unnormalized sum of rewards of the policy sets Π_{15} and Π_{24}, and DQN in a lifelong RL setting described in the text. Shadowed regions are one standard error over 100 runs.