Transfer Learning in Deep Reinforcement Learning: A Survey

Zhuangdi Zhu, Kaixiang Lin, and Jiayu Zhou

Abstract—This paper surveys the field of transfer learning in the problem setting of Reinforcement Learning (RL). RL has been a key solution to sequential decision-making problems. Along with the fast advances of RL in various domains, such as robotics and game-playing, transfer learning arises as an important technique to assist RL by leveraging and transferring external expertise to boost the learning process of RL. In this survey, we review the central issues of transfer learning in the RL domain, providing a systematic categorization of its state-of-the-art techniques. We analyze their goals, methodologies, applications, and the RL frameworks under which the transfer learning techniques are approachable. We discuss the relationship between transfer learning and other relevant topics from the RL perspective, and also explore the potential challenges as well as future development directions for transfer learning in RL.

Index Terms—Transfer Learning, Reinforcement Learning, Survey, Machine Learning.

1 Introduction

Reinforcement Learning (RL) has been considered as a principled and effective framework to solve sequential decision-making tasks, where a learning agent interacts with an environment to improve its performance through trial and error [1]. Originated from cybernetics and has blossomed in Computer Science, RL has been widely applied to both academia and industries to address challenging decision-making tasks which were previously intractable. Along its rapid developments come with challenges faced by RL, such as scalability. Traditional RL has difficulties in handling complex domains, such as tasks with image input. Scaling RL to more practical and high dimensional domains becomes critical.

In the meanwhile, an integrated framework where Deep Learning (DL) is applied to serve RL tasks has been widely studied and developed over recent years. DL resolves some challenges faced in RL with the ability of learning powerful function approximators, which can build low dimensional structures in high-dimensional feature space. The combined structure of DL and RL is referred to as Deep Reinforcement Learning (DRL) [2]. DL has enabled RL to scale to decision-making problems that were previously unresolvable and achieve great success in areas such as robotics control [3], [4] and game playing [5]. It also has a promising future in many domains, including health informatics [6], electricity networks [7], intelligent transportation systems [8], [9], and etc.

Besides its advances, DRL still face intriguing difficulties when applied to many real-world applications, such as high sample complexity. In practical RL applications, environment models are usually unknown, and an agent cannot exploit its knowledge of the environment to improve its performance

until enough interaction experiences are collected. Due to the issues of partial observability, sparsity and delay in the environment feedback, and high-dimensional observations and action spaces, the cost of acquiring interaction samples can be prohibitive, and can even incur safety concerns in many real-world domains such as automatic driving and health informatics. All these issues motivated us to leverage the prior knowledge to improve the learning process of DRL. Therefore, *Transfer Learning* (TL), as a technique to utilize external expertise to accelerate the learning process, becomes an essential topic in RL.

TL has been extensively studied in the Supervised Learning (SL) domain [10]. Compared to an SL scenario, TL in RL, especially in DRL, is considered to be more complicated due to the components involved in an MDP environment. Especially, components of the MDP where the knowledge comes from, may be very different from where the knowledge transfers to. Moreover, expert knowledge can also take different forms and get transferred in different ways, especially in the case of deep neural networks.

With the rapid advances of DRL, previous efforts on summarizing TL approaches for RL do not include the up-to-date developments in DRL [11], [12]. Noticing all these different angles and possibilities, we comprehensively summarize the recent developments of *Transfer Learning in Deep Reinforcement Learning (TL in DRL)* domain. We categorize them into different sub-topics, review the theories and applications of each, and draw connections among them.

The rest of this survey is organized as follows: In section 2, we introduce the background of RL, key DRL algorithms, and define important terminologies that will be used through this survey. Next, we clarify the definition of TL in the RL domain. We also briefly introduce related research fields that are different from but draw close connections to TL (Section 2.4). In Section 3, we take versatile perspectives to evaluate TL approaches, by providing different ways to categorize these approaches (Section 3.1), discussing potential differences between the source and target during transfer (Section 3.2), and summarizing popular metrics for evaluating TL

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effectiveness (Section 3.3). Section 4 elaborates recent TL approaches in the DRL domain. Discussed contents in this section are organized by the form of transferred knowledge, such as shaped rewards (Section 4.1), expert demonstrations (Section 4.2), teacher policies (Section 4.3). We also organize some TL approaches by the way transfer happens, such as inter-task mapping (Section 4.4), learning transferrable representations (Section 4.5 and 4.6), and etc. We discuss the applications of TL in DRL in Section 5 and provide some future perspectives worth researching in Section 6.

2 DEEP REINFORCEMENT LEARNING AND TRANS-FER LEARNING

In this section, we first give a brief overview of the developments in RL and DRL and provide some key terminologies used throughout this survey. Next, we provide different perspectives to categorize TL approaches. We also discuss some research domains which are not elaborated in this survey but are relevant to TL.

2.1 Reinforcement Learning Preliminaries

A typical RL problem can be considered as training an agent to interact with an environment that satisfies the criterion of a **Markov Decision Process (MPD)** [13]. From each interaction with the MDP, the agent starts with an initial *state* and performs an *action* accordingly, which yields a *reward* to guide the agent actions. Once the action is taken, the MDP transits to the next state by following the underlying *transition dynamics* of the MDP. The agent accumulates the time-discounted rewards along its interactions with the MDP. We call a subsequence of interactions as an *episode*. For MDPs with infinite horizons, we assume that there are *absorbing states*. Any action taken upon an absorbing state will only lead to itself and yields zero rewards [1]. All abovementioned components in this MDP can be represented as a tuple $\mathcal{M} = (\mu_0, \mathcal{S}, \mathcal{A}, \mathcal{T}, \gamma, \mathcal{R}, \mathcal{S}_0)$, where:

- μ_0 is the set of **initial states**.
- S is the state space.
- *A* is the **action** space.
- $\mathcal{T}: S \times A \times S \to \mathbb{R}$ is the transition probability distribution, where T(s,a,s') = P(s'|s,a) specifies the probability of the state transitioning to s' upon taking action a in state s.
- $\mathcal{R}: S \times A \times S \to \mathbb{R}$ is the **reward distribution**, where R(s, a, s') is the reward an agent can get by taking action a in state s with the next state being s'.
- γ is a discounted factor, $\gamma \in (0,1]$.
- S_0 is the set of **absorbing states**.

Without ambiguity, we will refer *MDPs* and *tasks* interchangeably through this survey. An RL agent behaves in $\mathcal M$ by following its policy π , which is a function over states to actions: $\pi:\mathcal S\to\mathcal A$, where $\pi(a|s)$ specifies the probability for agent taking action a upon receiving state s. Each policy π is associated with a **value function**, which is defined over states:

$$V_M^{\pi}(s) = \mathbb{E}[r_0 + \gamma r_1 + \gamma^2 r_2 + \dots; \pi, s],$$

where $r_i = R(s_i, a_i, s_{i+1})$ is the reward that an agent receives by taking action a_i in the *i*-th state s_i ,

and the next state transits to s_{i+1} . The expectation $\mathbb E$ is taken over $s_0 \sim \mu_0, a_i \sim \pi(a_i|s_i), s_{i+1} \sim P(s_i, a_i, s_{i+1})$. The value-function estimates the quality of being in state s, by evaluating the expected rewards that an agent can get since s, given that the agent follows policy π in environment $\mathcal M$. Similar to the value-function, each policy also carries a Q-function, which is defined over both states and actions, and therefore estimates the quality of taking action a in state s:

$$Q_M^{\pi}(s, a) = \mathbb{E}_{s \sim P(s, a, s')}(R(s, a, s') + \gamma V_M^{\pi}(s')).$$

The objective for an RL agent is to learn an optimal policy π_M^* that maximizes the expectation of accumulated discounted rewards:

$$\begin{split} \pi_M^\pi(s) &= \underset{a \in A}{\arg\max} \ \ Q_M^*(s,a), \\ \text{where } Q_M^*(s,a) &= \underset{\pi}{\sup} \ \ Q_M^\pi(s,a). \end{split}$$

2.2 Reinforcement Learning Algorithms

In this section, we briefly review some key RL algorithms introduced during the recent decades, as they are the cornerstones for the TL approaches mentioned in this survey. Notice that any RL problem can be divided into two subtasks: prediction and control [1]. The prediction step is for evaluating the quality of the current policy, which can be done by either policy evaluation or value evaluation. The latter step is also referred to as policy Improvement, as the policy is improved in this step by adjusting its action selections based on the result from the first step. Policies can be improved by combining these two steps together iteratively. This procedure is therefore called policy iteration.

Monte-Carlo Methods are model-free approaches, which means the target policy is optimized using samples of interactions with the environment, without requiring knowledge of the MDP's transition dynamics. Monte-Carlo methods use samples of episodes to estimate the value of each state based on episodes starting from that state. Monte-Carlo methods can be off-policy, if the episodic samples are collected by a behavior policy which are different from the target policy considered by the current learning step. They can also be on-policy, when the samples are collected by following the target policy. Importance sampling is usually applied to the off-policy approaches in order to transform the expectation of returns from the behavior policy to the target policy [14], [15].

Temporal-Difference Learning, or TD-learning for short, is an alternative to Monte-Carlo methods for solving the prediction problem. The key idea behind TD-learning is to learn the state quality function by bootstrapping, which means it updates its estimation of the function based on another estimation. It can also be extended to solve the control problem, so that both value function and policy can get improved. TD-learning is one of the most widely used RL frameworks due to its simplicity and general applicability. Examples of on-policy TD-learning algorithms include SARSA [16], Expected SARSA [17], Actor-Critic [18] and its variant called A3C [19]. Examples of off-policy TD-leaning approaches are Q-learning [20] and its variants built with deep-neural networks, such as DQN [21], Double-DQN [21], and etc.

Most TD-learning approaches are *one-step bootstrapping*, which are also named TD(0) methods. There also exist n-step TD-learning approaches with $n \geq 1$ being the number of bootstrap steps. A similar but more general framework is called *eligibility traces*. It draws a rainbow between TD(0) and Monte-Carlo methods and approaches to the latter when $n \to \infty$. It inherits the advantage of Monte-Carlo methods by being able to solve non-MDP tasks, and at the same time addresses the issue of delayed rewards due to its resemblance to TD-learning approaches. Examples of Q-learning variations with eligibility traces, called $Q(\lambda)$, are the work done by [22] [23], and [1].

Policy Gradient is a different mechanism compared with action-value based approaches. It learns a parameterized policy directly and updates its parameters to find optimal policies. One example of policy-gradient approach is *RE-INFORCE* [24]. Recent years has witnessed the presence of various policy-gradient approaches thanks to the rapid development of DL, such as *Trust region policy optimization* (*TRPO*) [25], Actor-Critic, and *Proximal Policy optimization* (*PPO*) [26]. One advantage of policy gradient methods is that they are more suitable for tasks with continuous state and action spaces. Representative algorithms are *Deterministic policy gradient* (*DPG*) [27] and its extensions including *DDPG* [28] and *Twin Delayed DDPG* [29].

2.3 Transfer Learning in Deep Reinforcement Learning

Remark 1. Without losing clarify, in the rest of this survey, we will equivalently refer the MDP as the domain, the task, or the environment.

Let \mathcal{M}_s a set of source MDPs, from which the prior knowledge \mathcal{D}_s is accessible in the target domain \mathcal{M}_t , such that by leveraging such information \mathcal{D}_s , the agent performs better in \mathcal{M}_t compared with not utilizing it. We use $\mathcal{M}_s \in \mathcal{M}_s$ to refer to a single source MPD. For the simplistic case, knowledge can transfer between two agents within the same MDP, which results in $|\mathcal{M}_s|=1$, and $\mathcal{M}_s=\mathcal{M}_t$. More concretely, we provide the following definition of TL from the DRL perspective:

Definition 1. (Transfer Learning) Given a set of source domain \mathcal{M}_s and a target domain \mathcal{M}_t , Transfer Learning aims to learn an optimal policy π^* for the target domain, by leveraging exterior information \mathcal{D}_s from \mathcal{M}_s as well as interior information \mathcal{D}_t from \mathcal{M}_t :

$$\pi^* = \operatorname*{arg\,max}_{\pi} \mathbb{E}_{s \sim \mu_0^t, a \sim \pi}[Q_{\mathcal{M}}^{\pi}(s, a)],$$
 where $\pi = \phi_{\mathrm{DL}}(\mathcal{D}_s \sim \mathcal{M}_s, \mathcal{D}_t \sim \mathcal{M}_t).$

 $\pi: \mathcal{S}^t \to \mathcal{A}^t$ is a function mapping from the states to actions w.r.t the target domain \mathcal{M}_t , and is approximated using deep neural networks trained on both \mathcal{D}_t and \mathcal{D}_s . For regular DRL without transfer learning, we can consider it as $\mathcal{D}_s = \emptyset$, where a policy π is learned purely on \mathcal{D}_t , with $\pi = \phi_{\mathrm{DL}}(\mathcal{D}_t)$.

2.4 Related Topics

Along with TL, there have been other approaches to address RL by leveraging different forms of supervision under different problem settings. In this section, we briefly discuss

some techniques that are relevant to TL but are not elaborated in this survey. We will analyze the difference as well as connections between TL and these relevant techniques in the RL domain, which we hope can further clarify the scope of this survey.

Imitation Learning aims to train a policy to mimic the behavior of an expert given only the demonstrations from that expert. Also known as Apprenticeship Learning, Imitation Learning is considered as an alternative to RL to solve sequential decision-making problems. Different from TL, conventional Imitation Learning approaches only learn from external demonstrations (\mathcal{D}_s), without knowing the target environment rewards (\mathcal{D}_t) [30]. There are currently two main paradigms for imitation learning. The first one is Behavior Cloning, where a policy is trained as a supervise-learning task without access to any reinforcement learning signal [31]. The second is *Inverse Reinforcement Learning*, where the goal of imitation learning is to recover a reward function of the MDP that can explain the behavior of the expert demonstrator [32]. Imitation Learning is also closely related to an TL approach called *Learning from Demonstrations (LfD)* (Sec 4.2). What distinguishes LfD and the classic *Imitation* Learning approach is that, LfD occurs during real interactions with the RL environment with reward feedback signals, in the hope of efficient policy improvements assisted by expert demonstrations, rather than recovering the ground-truth reward functions or the expert policy represented by the given demonstrations.

Lifelong Learning refers to the ability of learn multiple temporal or spatial related tasks given non-stationary information streams. The key to acquiring Lifelong Learning is a tradeoff between obtaining new information over time and retaining previously learned knowledge to transfer across new tasks. The notion of Lifelong Learning is applicable to both traditional machine learning [33] and RL [34], [35], where the later is closely related to the topic of Meta Reinforcement Learning [36]. Lifelong Learning is a more challenging task compared with TL, mainly because it requires an agent with the ability of transferring knowledge to dynamically-changing, unseen tasks, instead of a fixed target task. Moreover, the ability of automatic task detection can also be a requirement in the Lifelong Learning framework [37], whereas for TL the agent is usually notified of the emergence of a new task.

Hierarchical Reinforcement Learning (HRL) is more suitable for restoring the real-world tasks which are usually hierarchical. Different from traditional RL, in an HRL setting, the action space is grouped into different granularities to form higher-level macro actions. Accordingly, the learning task is also decomposed into hierarchically dependent subgoals. Most well-known HRL framework includes the Feudal learning [38], Options framework [39], Hierarchical Abstract Machines [40], and MAXQ [41]. With higher-level abstraction on tasks, actions, and state spaces, HRL facilitates knowledge transfer across similar domains. In this survey, however, we focus on discussing approaches of TL for general RL tasks rather than HRL.

Multi-Agent Reinforcement Learning (MARL) has strong connections with *Game Theory* [42] and is closely related to single-agent RL. MARL considers an MDP with multiple agents performing simultaneously in the environment, in order to solve problems which were difficult or infeasible to

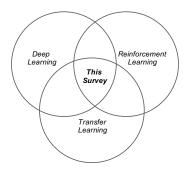


Fig. 1: Scope of this survey.

be addressed by a single agent [43]. The interactive mode for multiple agents can be either independent, cooperative, competitive, or even a hybrid setting [44]. Approaches of knowledge transfer for MARL falls into two classes: interagent transfer and intra-agent transfer. We refer to [45] for a more comprehensive survey of this topic. Different form their perspective, this survey emphasizes on the general TL approaches for a single agent scenario, although approaches mentioned in this survey may also be applicable to multiagent MPDs.

3 EVALUATING TRANSFER LEARNING APPROACHES IN DEEP REINFORCEMENT LEARNING

3.1 Approach Categorization

In this section we categorize different TL approaches by analyzing the following key questions:

- What knowledge has been transferred: Knowledge comes from the source domain and can take different forms of supervisions, such as a set of expert experiences, the action probability distribution of an expert policy, or even a potential function that estimates the quality of state and action pairs in the source/target MDP. These divergences in knowledge forms and granularities affect the internal logic of different TL methods. The quality of the transferred knowledge, e.g, whether it comes from an oracle policy or suboptimal human demonstrations, also affects the way we design TL methods.
- Where the transfer occurs: For arbitrary RL task, the MDP (environment) can be defined as a tuple of $\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{T}, \gamma, \mathcal{R})$. The source MDP \mathcal{M}_s is the place where the prior knowledge comes from and the target MDP \mathcal{M}_t is where the knowledge is transferred to. Some TL approaches suit the case where \mathcal{M}_s and \mathcal{M}_t are equivalent, whereas others are designed to transfer knowledge between different MPDs. The difference between \mathcal{M}_s and \mathcal{M}_t varies per task. For example, in some game tasks where observations are RGB pixels, \mathcal{M}_s and \mathcal{M}_t can share the same \mathcal{A} but differs in the observation space. For approaches such as potential-based reward shaping, the two MDPs differ only by the reward distribution: $\mathcal{R}_s \neq \mathcal{R}_t$. These similarity gaps determine the difficulty of transfer learning, and how much ratio of knowledge can be transferred from \mathcal{M}_s to \mathcal{M}_t .

- How to transfer knowledge between source and target MPDs: This question can be rephrased as different sub-questions, such as: What assumptions have been made on the similarity of \mathcal{M}_s to \mathcal{M}_t ? Is the mapping function from \mathcal{M}_s to \mathcal{M}_t pre-defined or autonomous generated? What components of the learning procedure, e.g, learning the policy π , the value function V, or even the transition dynamics \mathcal{T} (for model-based RL), can benefit from the transferred knowledge? Is the mapping learned offline or online [46]?
- What goal to achieve for the transfer learning approach: We can answer this question by analyzing two aspects of an TL approach: (i) its optimization objective function, and (ii) its evaluation metrics. Evaluation metrics can be the initial/convergence/episodic performance, or the training iterations/samples used to reach a certain threshold. On the other hand, the objective function that defines the optimization goal may also differ, due to adopting different regularization constraints, or due to difference in the transferred knowledge. For example, maximizing the policy entropy can be augmented into the main learning objective, in order to encourage explorations when the transferred knowledge are imperfect demonstrations [47].
- How applicable a TL approach is: We can rephrase
 this question as other forms, e.g., Is the TL approach
 policy-agnostic, or applicable only to certain set of
 algorithms, e.g, Temporal Difference (TD) methods?
 Answers to this question are closely related to the
 form of the transferred knowledge and the similarity
 between two MDPs.
- What is the accessibility of the target MDP: We assume that the cost of accessing knowledge from source domains are cheaper. However, the learning agent may not be able to access the target MDP directly, or it can only have a very limited number of MDP interactions, due to the high sampling cost in the target MDP. Examples of this scenario include learning an auto-driving agent for real scenarios after training it in simulated platforms [48], or training a navigation robot using simulated image inputs before letting it adapt to real environments [49].
- How sample efficient the TL approach is: This question is related to the above question regarding the accessibility of a target MDP. Based on the number of interactions needed to enable TL, we can categorize TL techniques into the following classes: (i) Zero-shot transfer: the learned agent are directly applicable to the target MDP without requiring any interactions with it; (ii) Few-shot transfer: only a few samples (interactions) are needed from the target MDP; (iii) Sample-efficient transfer: most of other algorithms fall into this category, where an agent can benefit from TL to learn faster with fewer interactions, which is therefore more sample efficient, compared with a standard RL procedure without any knowledge transfer. Compared with training from scratch in the target MDP, TL approach enable the target agent with a better initial performance and/or converge faster

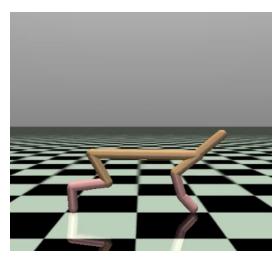


Fig. 2: The illustration of the HalfCheetah benchmark. The agent is trained to run as fast as possible while keeping a balance to not hurting itself.

with the guidance of the transferred knowledge.

3.2 Potential Differences Among Tasks

During TL, the differences between the source and target task may reside in any components that form a MDP. In this section, we will use *HalfCheetah*, a standard RL benchmark from OpenAI gym, as a running example to illustrate those differences. *HalfCheetah*¹ is physical locomotion task. As shown in Figure 2, the objective of HalfCheetah is to train a two-leg agent to run as fast as possible without losing control of itself. A learning task can be made different by changing the following components:

- S (State-space): extend or limit the available positions for the agent to move to; change the available range of angle velocities.
- A (Action-space): change the range of available torques for the thigh, shin, or foot.
- R (Reward function): simplify the task by using only distance moved forward as rewards, or complicate the task by using the scale of accelerated velocity in each direction as penalty costs.
- T (Transition dynamics): change the physical rules followed in the task environment; or change the transition probability to be dependent on partial state variables.
- Task objectives: change the objective to be move as far as possible regardless of the direction the agent moves to.
- μ₀ (Initial states): where and with what posture the agent starts.
- τ (Trajectories): limit or extend the number of steps the agent is allowed to move.

3.3 Evaluation metrics

We enumerate the following dominant metrics for evaluating the effectiveness of TL approaches, of which the first four have also been summarized in prior work [50], [11]:

1. https://gym.openai.com/envs/HalfCheetah-v2/

- *Jumpstart Performance* (*jp*): the initial performance (returns) of the agent with and without knowledge transfer.
- Asymptotic Performance (ap): the ultimate performance (returns) of the agent with and without knowledge transfer.
- Accumulated Rewards (ar): the area under the learning curve of the agent with and without knowledge transfer
- *Transfer Ratio* (*tr*: the ratio between *ap* of the agent with TL and *ap* of the agent without TL.
- Time to Threshold (tt): the learning time (iterations) needed for the target agent to reach certain performance thresholds, with and without knowledge transfer.
- *Performance with Fixed Training Epochs(pe)*: the performance achieved by the target agent after a specific number of training iterations, with and without TL.
- *Performance Sensitivity(ps)*: the variance in returns using different hyper-parameter settings, with and without TL.

In addition to the abovementioned criteria which focus mainly on the *learning curve* of the learning agent, we consider that evaluating TL techniques from the perspective of *transferred knowledge* is also important. Accordingly, we summarize the following metrics, which although has not been explicitly discussed by any prior art:

- Required Knowledge Quantity (rkqt): i.e. the necessary amount of the knowledge required for TL in order to achieve certain performance thresholds. Representative metrics along this line include the number of designed source tasks, the number of expert policies, or the number of demonstrated interactions utilized to enable the knowledge transfer.
- Required Knowledge Quality (rkql): the quality of the knowledge required to enable effective TL. This metric helps in answering questions such as (i) Does the TL approach rely on near-oracle knowledge from the source domain, such as expert-level demonstrations/policies, or (ii) does the TL technique work even given sub-optimal knowledge?

Metrics from the resource perspective are harder to standardize, because TL approaches differ in various perspectives, including the form of transferred knowledge, the RL framework utilized to enable the transfer, and the difference between the source and the target MDP. It may lead to biased evaluations by comparing TL approaches from just one aspect. However, we believe that explicating these resource-related metrics will help in designing more generalizable and efficient TL approaches.

In general, most of the abovementioned metrics can be considered as evaluating two abilities of a TL approach: the *Mastery* and *Generalization* ability. *Mastery* refers to how well the learned agent can ultimately perform in the target MDP, while *Generalization* is about the ability of the learning agent to quickly adapt to target MDPs assisted by knowledge from the source domain. Metrics, such as ap, ar and tr, are embodiment of the *Mastery* ability, whereas metrics of jp, ps, rkqt and rkql illustrate the *Generalization* ability. Metrics such

as tt, for example, can measure either the Mastery ability or the Generalization ability, depending on the choice of different thresholds. tt with a threshold approaching to the optimal emphasizes more on the Mastery, while a lower threshold may focus on the Generalization ability. Equivalently, pe can also focus on either side depending on the choice of the number of training epochs.

4 Transfer Learning Approaches

4.1 Reward Shaping

In this section, we review TL methods in the form of Reward Shaping (RS). We start to introduce TL approaches with RS, because it is generally applicable to different RL algorithms and require minimal change to the underline RL framework. RS leverages prior knowledge to reconstruct the reward distributions for the target MDP to bias the agent's action selections. In addition to learning on the environment feedbacks, RS learns a reward-shaping function $\mathcal{F}: \mathcal{S} \times \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ to generate auxiliary rewards, provided that the additional rewards contain prior knowledge to guide the agent for better action choices. Intuitively, visiting beneficial states will get higher extra rewards, which can navigate the agent to desired trajectories. The agent will learn its policy using the newly shaped rewards \mathcal{R}' : $\mathcal{R}' = \mathcal{R} + \mathcal{F}$. Accordingly, by reward shaping the agent learns its policy in a modified MDP where the only difference is the reward function:

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, \mathcal{T}, \gamma, \mathcal{R})) \to \mathcal{M}' = (\mathcal{S}, \mathcal{A}, \mathcal{T}, \gamma, \mathcal{R}').$$

Potential based Reward Shaping (PBRS) is the most classical RS approach. [51] proposed PBRS to form the shaping function F as the difference between two potential functions Φ :

$$F(s, a, s') = \gamma \Phi(s') - \Phi(s),$$

where $\Phi(s)$ comes from the knowledge of expertise and evaluates the quality of a given state. The structure of potential difference addresses the cycle dilemma mentioned in [52], in which an agent can get positive rewards by following a sequence of states which forms a cycle: $\{s_1, s_2, s_3, \ldots, s_n, s_1\}$ with $F(s_1, a_1, s_2) + F(s_2, a_2, s_3) + \cdots + F(s_{n-1}, a_{n-1}, s_1) > 0$. A potential based F avoids this issue by providing any state cycle with no more than zero extra rewards: $\sum_{i=1}^{n-1} F(s_i, a_i, s_{i+1}) \leq -F(s_n, a_n, s_1)$. It has been proved that without further restrictions on the underlying MDP or the shaping function F, PBRS is sufficient and necessary to preserve the policy invariance. Moreover, the optimal Q function in the original and transformed MDP are related by the potential function:

$$Q_{M'}^*(s,a) = Q_M^*(s,a) - \Phi(s). \tag{1}$$

Equation 1 draws a connection between potential based reward-shaping and advantage-based learning approaches [53].

Vanilla *PBRS* was extended by [54], which formulated the potential as a function of both state and actions. This approach is called *Potential Based state-action Advice*

(PBA). $\Phi(s,a)$ therefore evaluates how beneficial it is to take action a on state s:

$$F(s, a, s', a') = \gamma \Phi(s', a') - \Phi(s, a).$$
 (2)

One limitation of PBA is that it requires on-policy learning, as in Equation (2), a' is the action to take upon transitioning to the next state s' by following the learning policy. Similar to Equation (1), the optimal Q functions in both MDPs are related by the difference of potentials: $Q_{M'}^*(s,a) = Q_M^*(s,a) - \Phi(s,a)$. Once the optimal policy in M' is learned, the optimal policy in M can be recovered:

$$\pi_M^{\pi}(s) = \underset{a \in A}{\operatorname{argmax}} \ (Q_M^*(s, a) - \Phi(s, a)).$$

All abovementioned RS approaches assume a static potential function. [55] proposed a *Dynamic Potential Based (DPB)* approach which makes the potential a function of both state and time: $F(s,t,s',t')=\gamma\Phi(s',t')-\Phi(s,t)$. They proved that this dynamic approach can still maintain policy invariance: $Q_{M'}^*(s,a)=Q_M^*(s,a)-\Phi(s,t)$, where t is the current time.

[56] later introduced a way to incorporate any prior knowledge into a dynamic potential function structure. Their approach is called *Dynamic value-function Advice (DPBA)*. The underline rationale is that, given any extra reward function R^+ from prior knowledge, in order to add this extra reward to the original immediate reward, the potential function should satisfy:

$$\gamma \Phi(s', a') - \Phi(s, a) = F(s, a) = R^{+}(s, a).$$

If Φ is not static, but learned as an extra state-action value function overtime, then the Bellman Equation for Φ is :

$$\Phi^{\pi}(s, a) = r^{\Phi}(s, a) + \gamma \Phi(s', a').$$

which intuitively shows that the shaping rewards F(s,a) is just the negation of $r^{\Phi}(s,a)$:

$$F(s, a) = \gamma \Phi(s', a') - \Phi(s, a) = -r^{\Phi}(s, a).$$

This leads to the approach of using the negation of R^+ as the immediate reward to train an extra state-action value function Φ and the policy simultaneously, with $r^{\Phi}(s,a) = -R^+(s,a)$. Φ will be updated by a residual term $\delta(\Phi)$:

$$\Phi(s, a) \leftarrow \Phi(s, a) + \beta \delta(\Phi),$$

where $\delta(\Phi)=-R^+(s,a)+\gamma\Phi(s',a')-\Phi(s,a)$, and β is the learning rate. Accordingly, the dynamic potential function F is:

$$F_t(s, a) = \gamma \Phi_{t+1}(s', a') - \Phi_t(s, a).$$

The advantage of DPBA is that it provides a framework to allow arbitrary knowledge to be shaped as auxiliary rewards. However, it requires learning an extra state-action value $\Phi(s,a)$ in parallel while learning the target policy. It has been further proved that when Φ converges to a TD-fix point Φ^π , the provided reward is in the form of $R^+(s,a)$ augmented with a bias term:

$$F(s, a, s', a') = R^{+}(s, a) + \gamma(\Phi^{\pi}(s', a') - \mathbf{E}[\Phi^{\pi}(s', a')]).$$

Work along this line mainly focused on designing different shaping functions F(s,a), while what knowledge

can be used to derive this function is off the table. One work by [57] proposed to use RS to transfer an expert policy from source \mathcal{M}_s to target \mathcal{M}_t . The authors assumed the existence of two mapping functions, M_S and M_A , which can transform the state and action from the source task to the target task. Then the augmented reward is just $\pi_s((M_S(s), M_A(a)))$, which is the probability that the mapped state and action will be taken by the expert policy in the source domain. Two different RS frameworks have been considered to integrate this augmented reward. One is to follow the PBA approach to build the potential function directly as: $\Phi(s,a) = \pi_s((M_S(s), M_A(a)))$. The other is to follow the idea of DPBA by learning an extra state-action value function, where the immediate reward is the negation of $\pi_s((M_S(s), M_A(a)))$.

Another work uses demonstrated interactions sampled from an expert policy to shape rewards [58]. The way they build the augmented reward involves a discriminator, which is trained to distinguish samples from the given expert policy and samples from the target policy, and the loss of the discriminator is applied to shape the reward to encourage the learning agent to mimic the expert behavior. This work is a combination of two transfer learning approaches: RS and Learning from Demonstrations, the later of which will be elaborated in Section 4.2.

Besides the single-agent and model-free RL scheme, there has also emerged work which applies RS to multi-agent RL [59], model-based RL [60], and hierarchical RL [61]. Especially, [59] extended the idea of RS to multi-agent systems, showing that the Nash Equilibria of the underlying stochastic game is unchanged under a potential-based reward shaping structure. [60] applied RS to a model-based RL setting, where the potential function is learned based on the *free space assumption*, an approach to model transition dynamics in the environment. [61] integrated RS to *MAXQ*, which is a hierarchical RL algorithm framework, by augmenting the extra reward onto the completion function of the MAXQ [41].

The abovementioned work is based on a consensus that the knowledge for the shaped reward comes *externally*, which enables TL to take effect. Some work of RS also considers the scenario where the augmented reward comes *intrinsically*, such as the *Belief Reward Shaping* proposed by [62], which utilized a Bayesian reward shaping framework to generate the potential value that decays with experience, where the potential value comes from the critic itself.

In general, most RS approaches follow the potential based RS principle which has been developed systematically: from the classical PBRS which is built on a static potential shaping function over *states*, to *PBA*, which generates potential as a function over both states and actions, and DPB, which allows a dynamic potential function over states and time, to the state-of-the-art DPBA, which allows a dynamic potential over states and actions to be learned as an extra stateaction value function in parallel with the environment value function. As as an effective TL paradigm, RS has been widely applied to many fields such as robot training [63], spoken dialogue systems [64], and question answering [65]. It provides a feasible framework to transfer knowledge as the augmented reward and is generally applicable to almost all RS algorithms. How to integrate RS with other TL approaches, such as Learning from demonstrations (Section

4.2) and *Policy Transfer* (Section 4.3) to build the potential function for shaping will be a interesting topic of ongoing research.

4.2 Learning from Demonstrations

In this section, we review TL techniques in which the transferred knowledge takes the form of external demonstrations. The demonstrations may come from different sources with different qualities. It can come from a human expert, a near-optimal expert policy, or even a suboptimal policy. We use D_E to denote such set of demonstrations, with each element in D_E a tuple of transition: $(s,a,s',r) \in D_E$. Most work along this line addresses a specific TL scenario, i.e. the source and target MDPs are the same: $\mathcal{M}_s = \mathcal{M}_t$, although there has been work that learns from demonstrations in a different MDP [66].

In general, learning from demonstrations (LfD) is a technique to assist RL by utilizing provided demonstrations for more efficient exploration. Knowledge conveyed in demonstrations encourages agents to explore states which can benefit its policy learning procedure. Depending on when the demonstrations are used for knowledge transfer, approaches can be divided into offline methods and on-line methods. For offline approach, demonstrations are used for pre-training RL components before the RL learning step. RL components such as value function V(s) [67], policy π [68], or even the model of transition dynamics [69], are initialized by supervised learning using these demonstrations. For the online approach, demonstrations are directly used in the RL stage to bias the agent actions for efficient explorations [70]. Most work discussed in this section follows the online transfer pattern, or combines the offline pre-training with online RL learning [71]. Depending on *what* RL frameworks are used to enable knowledge transfer, work in this domain can be categorized into different branches: some adopts the policy-iteration framework [72]-[74], others follow a Q-learning framework [70], [75], while more recent work follows the policy-gradient framework [58], [71], [76], [77].

Demonstration data have been applied in the *Policy Iterations* framework by [78]. Later, [72] introduced the *Direct Policy Iteration with Demonstrations (DPID)* algorithm. This approach samples complete demonstrated rollouts D_E from an expert policy π_E , in combination with the self-generated rollouts D_π gathered from the environment. $D_\pi \cup D_E$ are used to generate a Monte-Carlo estimation of the Q-value: \hat{Q} , from which a learning policy can be derived greedily: $\pi(s) = \arg\max_{a \in \mathcal{A}} \hat{Q}(s,a)$. This policy π is further biased by a loss function $\mathcal{L}(s,\pi_E)$ to minimize the discrepancy from the expert policy decision:

$$\mathcal{L}(\pi, \pi_E) = \frac{1}{N_E} \sum_{i=1}^{N_E} \mathbb{1}\{\pi_E(s_i) \neq \pi(s_i)\}.$$

where N_E is the number of expert demonstration samples, and $\mathbb{1}(x)$ is an indicator function.

Another work along this line includes the *Approximate Policy Iteration with Demonstration (APID)* algorithm proposed by [73] and its extension [74]. Different from *DPID* where both D_E and D_{π} were used for value estimation, the *APID* algorithm applies only D_{π} to approximate on the Q function.

Methods	MDP Difference	Format of shaping reward	Knowledge source
PBRS	$\mathcal{M}_s = \mathcal{M}_t$	$F = \gamma \Phi(s') - \Phi(s)$	Х
PBA	$\mathcal{M}_s = \mathcal{M}_t$	$F = \gamma \Phi(s', a') - \Phi(s, a)$	Х
DPB	$\mathcal{M}_s = \mathcal{M}_t$	$F = \gamma \Phi(s', t') - \Phi(s, t)$	Х
DPBA	$\mathcal{M}_s = \mathcal{M}_t$	$F_t = \gamma \Phi_{t+1}(s', a') - \Phi_t(s, a) ,$	Х
		Φ learned as an extra Q function	
[57]	$S_s \neq S_t$, $A_s \neq A_t$	$F_t = \gamma \Phi_{t+1}(s', a') - \Phi_t(s, a)$	π_s
[58]	$\mathcal{M}_s = \mathcal{M}_t$	$F_t = \gamma \Phi_{t+1}(s', a') - \Phi_t(s, a)$	D_E

TABLE 1: A comparison of reward shaping approaches.

The expert demonstrations D_E are used to learn the value function, which intuitively, given any state s_i , renders expert actions $\pi_E(s_i)$ with higher Q-value margins compared with other actions that are not shown in D_E :

$$Q(s_i, \pi_E(s_i)) - \max_{a \in \mathcal{A} \setminus \pi_E(s_i)} Q(s_i, a) \ge 1 - \xi_i.$$

The term ξ_i is used to account for the case of imperfect demonstrations. This value shaping idea is instantiated as an augmented hinge-loss to be minimized during the policy evaluation step:

$$\begin{split} Q \leftarrow \arg\min_{Q} f(Q), \text{ where } f(Q) = \\ \big\{ \mathcal{L}^{\pi}(Q) + \frac{\alpha}{N_{E}} \big[1 - (Q(s_{i}, \pi_{E}(s_{i})) - \max_{a \in \mathcal{A} \backslash \pi_{E}(s_{i})} Q(s_{i}, a)) \big]_{+} \big\}, \end{split}$$

in which $[z]_+ = \max\{0, z\}$ is the hinge loss, and $\mathcal{L}^{\pi}(Q)$ is the Q-function loss induced by an empirical norm of the optimal bellman residual:

$$\mathcal{L}^{\pi} = \mathbb{E}_{(s,a) \sim D_{\pi}} || \mathcal{T}^{\pi} Q(s,a) - Q(s,a) ||,$$

where $\mathcal{T}^{\pi}Q(s,a)=R(s,a)+\gamma\mathbb{E}_{s'\sim p(.|s,a)}[Q(s',\pi(s'))]$ is the bellman contracting operator. [74] further extend the work of *APID* with a different evaluation loss:

$$\mathcal{L}^{\pi} = \mathbb{E}_{(s,a) \sim D_{\pi}} || \mathcal{T}^* Q(s,a) - Q(s,a) ||,$$

where $\mathcal{T}^*Q(s,a) = R(s,a) + \gamma \mathbb{E}_{s' \sim p(.|s,a)}[\max_{a'} Q(s',a')]$. Their work theoretically convergence to the optimal Q function compared with APID, as \mathcal{L}_{π} is minimizing the Optimal Bellman Residual instead of the empirical norm.

In addition to policy iteration, the following two approaches integrate demonstration data into the TD-learning framework, such as *Q-learning*. Specifically, [70] proposed the *Deep Q-learning from Demonstration (DQfD)* algorithm, which maintains two separate replay buffers to store demonstrated data and self-generated data, so that expert demonstrations can always be sampled with a certain proportion along with the exploration data. Their work leverages the refined priority replay mechanism [79] where the probability of sampling a transition i is based on its priority p_i with a temperature parameter α : $P(i) = \frac{p_i^{\alpha}}{\sum_k p_k^{\alpha}}$.

Another work under the Q-learning framework is proposed by [75]. Their work, dubbed as LfDS, draws a close connection to the Reward Shaping technique (Section (4.1). It builds the potential function based on a set of expert demonstrations, and the potential value of a given state-action pair is measured by the highest similarity between the given pair and the expert experiences. This augmented reward assigns more credits to state-actions that are more similar to expert demonstrations, which eventually encourage the agent for expert-like behavior.

Besides Q-learning, recent work has integrated demonstration transfer into the *policy gradient* framework [30], [58], [71], [76], [77]. A representative work along this line is *Generative Adversarial Imitation Learning (GAIL)* proposed by [30]. GAIL introduced the notion of *occupancy measure* d_{π} , which is the stationary state-action distributions derived from a policy π . Based on this notion, a new reward function is designed such that maximizing the accumulated new rewards encourages minimizing the distribution divergence between the *occupancy measure* of the current policy π and the expert policy π_E . Specifically, the new reward is learned by adversarial training [80]: a discriminator D is trained to distinguish interactions sampled from the current policy π and the expert policy π_E :

$$J_D = \max_{D: \mathcal{S} \times \mathcal{A} \to (0,1)} \mathbb{E}_{d_{\pi}} \log[1 - D(s,a)] + \mathbb{E}_{d_E} \log[D(s,a)]$$

Since π_E is unknown, its state-action distribution d_E is estimated based on the given expert demonstrations D_E . It has been proved that, for a optimized discriminator, its output satisfies $D(s,a)=\frac{d_\pi}{d_\pi+d_E}$. The output of the discriminator is used as new rewards to encourage distribution matching, with $r'(s,a)=-\log(1-D(s,a))$. The RL process is naturally altered to perform distribution matching by optimizing the following min-max objective:

$$\max_{\pi} \min_{D} J(\pi, D) := \mathbb{E}_{d_{\pi}} \log[1 - D(s, a)] + \mathbb{E}_{d_{E}} \log[D(s, a)]$$
$$:= -D_{JS}[d_{\pi}||d_{E}].$$

Although GAIL is more related to *imitation learning* than LfD, its philosophy of using expert demonstrations for distribution matching has inspired other LfD algorithms. For example, [76] extended GAIL with an algorithm called *POfD*, which combines the discriminator reward with environment reward, so that the the agent is trained to maximize the accumulated environment rewards (RL objective) as well as performing distribution matching (imitation learning objective):

$$\max_{\theta} = \mathbb{E}_{d_{\pi}}[r(s, a)] - \lambda D_{JS}[d_{\pi}||d_{E}]. \tag{3}$$

They further proved that optimizing Equation 3 is same as a dynamic reward shaping mechanism (Section 4.1):

$$\max_{\theta} = \mathbb{E}_{d_{\pi}}[r'(s, a)],$$

where $r'(s,a) = r(s,a) - \lambda \log(D_w(s,a))$ is the shaped reward.

Both GAIL and POfD are under an *on-policy* RL framework. To further improve the sample efficiency of TL, some *off-policy* algorithms have been proposed, such as *DDPGfD* [58] which is built upon the DDPG framework. DDPGfD shares a similar idea as *DQfD* in that they both use

a second replay buffer for storing demonstrated data, and each demonstrated sample holds a sampling priority p_i . For a demonstrated sample, its priority p_i is augmented with a constant bias $\epsilon_D>0$ in order to encourage more frequent sampling of expert demonstrations:

$$p_i = \delta_i^2 + \lambda \|\nabla_a Q(s_i, a_i | \theta^Q)\|^2 + \epsilon + \epsilon_D.$$

where δ_i is the TD residual for transition i, $\|\nabla_a Q(s_i, a_i|\theta^Q)\|^2$ is the loss applied to the actor, and ϵ is a small positive constant to ensure all transitions are sampled with some probability.

Another work also adopts the DDPG framework to learn from demonstrations [71]. Their approach differ from DDPGfD in that its objective function is augmented with a *Behavior Cloning Loss* to encourage imitating on provided demonstrations:

$$\mathcal{L}_{BC} = \sum_{i=1}^{|D_E|} ||\pi(s_i|\theta_\pi) - a_i||^2.$$

To address the issue of suboptimal demonstrations, the form of *Behavior Cloning Loss* is altered based on the critic output, so that only demonstration actions with higher Q values will lead to the loss penalty:

$$\mathcal{L}_{BC} = \sum_{i=1}^{|D_E|} ||\pi(s_i|\theta_\pi) - a_i||^2 \mathbb{1}[Q(s_i, a_i) > Q(s_i, \pi(s_i))].$$

There are several challenges faced by learning-fromdemonstrations. The first one is imperfect demonstrations. Previous approaches presume near-optimal demonstrations. However, demonstrations can also be biased estimations of the environment, or even from a sub-optimal policy [77]. Current solutions to imperfect demonstrations include altering the objective function. For example, [73] leverages the hinge-loss function to allow occasional violations of the property that $Q(s_i, \pi_E(s_i)) - \max_{a \in \mathcal{A} \setminus \pi_E(s_i)} Q(s_i, a) \geq 1$. Some other work uses regularizations on the objective to alleviate overfitting on biased data [70], [79]. A different strategy to confront the sub-optimality is using them only for early learning steps. Specifically, in the same spirit of GAIL, [77] proposed Self-Adaptive Imitation Learning (SAIL) to learn from sub-optimal demonstrations using generative adversarial training, while gradually selecting self-generated trajectories with high qualities to replace less superior demonstrations.

Another challenge faced by LfD is overfitting. Demonstrations may be provided in limited numbers, which results in the learning agent's lacking guidance on states that are unseen in the demonstration dataset. This challenge is reinforced in MDPs with sparse reward feedbacks, as the learning agent cannot obtain much supervision information from the environment either. This challenge is also closely related to the covariate drift issue [81] which is commonly seen in behavior cloning. Current efforts to address this challenge include encouraging explorations by using an entropy-regularized objective [47], decaying the effects of demonstration guidance by softening its regularization on policy learning over time [82], and introducing disagreement regularizations by training an ensemble of policies based on the given demonstrations, where the variance among policies serves as a cost (negative reward) function [83].

In general, demonstration data can help in both *offline* pre-training for better initialization and *online* RL for efficient exploration. During the RL learning phase, demonstration data can be used together with self-generated data to encourage expert-like behaviors (*DDPGfD*, *DQFD*), shape value functions (*APID*), or bias the policy update in the form of an auxiliary objective function (*PID,GAIL, POfD*). The current RL framework used for demonstration transfer includes policy iteration, Q-learning, and policy gradient. Developing more general demonstration transfer approaches that are agnostic to RL frameworks, and learning from suboptimal, limited demonstrations, would be the next focus in this domain.

4.3 Policy Transfer

In this section, we review TL approaches where the external knowledge is expert (teacher) policies from source tasks. Work discussed in this section is built on a *many-to-one* problem setting, which we formularize as below:

Problem Setting. (Policy Transfer) A set of source tasks $\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_K$ are provided along with their expert (teacher) policies: $\pi_{E_1}, \pi_{E_2}, \ldots, \pi_{E_K}$. A student policy π for a target domain is learned by transferring knowledge from each π_{E_i} , with $1 \leq i \leq K$.

For the *one-to-one* scenario with only one teacher policy, we can consider it as a special case of the above problem setting with K=1. We categorize recent work of policy transfer into two different techniques: policy distillation and policy reuse.

4.3.1 Transfer via Policy Distillation

Knowledge of teacher policies from one or multiple source domains can be *distilled* to a student agent. The term *distillation* in the RL domain is proposed by [84] as an approach of knowledge ensemble from multiple teacher models to a single student model. This technique is later extended from the field of supervised-learning to RL. Since the student model is usually shallower than its teachers and is able to perform across multiple teacher tasks, policy distillation is also considered as an effective approach of model compression [85] and multi-task RL [86].

Conventional RL policy distillation frameworks transfer the teacher policy in a supervised learning paradigm [86], [87]. Specifically, a student policy is learned by minimizing the divergence of actions distributions between the teacher policy π_E and student policy π_θ , which is denoted as $\mathcal{H}^{\times}(\pi_E(\tau_t)|\pi_\theta(\tau_t))$:

$$\min_{\theta} \mathbb{E}_{\tau \sim \pi_E} \left[\sum_{t=1}^{|\tau|} \nabla_{\theta} \mathcal{H}^{\times}(\pi_E(\tau_t) | \pi_{\theta}(\tau_t)) \right].$$

The above expectation is over trajectories sampled from the teacher policy π_E and is therefore named as *teacher distillation*. A typical instantiation of this framework is [86], where N teacher policies are learned for N source tasks separately, and each teacher yields a dataset $D^E = \{s_i, q_i\}_{i=0}^N$ consisting of observations (states) s and vectors of the corresponding q-values q, such that $q_i = [Q(s_i, a_1), Q(s_i, a_2), ... | a_j \in \mathcal{A}]$. Teacher policies are further distilled to a single student agent

Methods	Optimality Guarantee	Format of transferred demonstrations	RL framework
DQfD	×	cached transitions in the replay buffer	DQN
LfDS	×	reward shaping function	DQN
GAIL	1	reward shaping function: $-\lambda \log(1 - D(s, a))$	TRPO
POfD	√	reward shaping function:	TRPO, PPO
		$r(s,a) - \lambda \log(1 - D(s,a))$	
DDPGfD	√	Increasing sampling priority	DDPG
[71]	√	Increasing sampling priority and behavior	DDPG
		cloning loss	
DPID	√	indicator binary-loss : $\mathcal{L}(s_i) = \mathbb{1}\{\pi_E(s_i) \neq$	API
		$\pi(s_i)$	
APID	X	hinge loss on the marginal-loss: $\left[\mathcal{L}(Q,\pi,\pi_E)\right]_+$	API
APID extend	√	marginal-loss: $\mathcal{L}(Q,\pi,\pi_E)$	API
SAIL	Х	reward shaping function: $r(s, a) - \lambda \log(1 - D(s, a))$	Twin Delayed DDPG

TABLE 2: A comparison of learning from demonstration approaches.

 π_{θ} by minimizing the KL-Divergence between each teacher policy $\pi_{E_i}(a|s)$ and the student policy π_{θ} sequentially using the dataset D^E :

$$\min_{\theta} \mathcal{D}_{KL}(\pi^E | \pi_{\theta}) \approx \sum_{i=1}^{|D^E|} \operatorname{softmax}(\frac{\boldsymbol{q}_i^E}{\tau}) \ln(\frac{\operatorname{softmax}(\boldsymbol{q}_i^E)}{\operatorname{softmax}(\boldsymbol{q}_i^\theta)}).$$

A variant of the *teacher-distillation* approach is called *student distillation* [88], [89]. In its optimization objective, the expectation is taken over the trajectories sampled from the student policy instead of the teacher policy:

$$\min_{\theta} \mathbb{E}_{\tau \sim \pi_{\theta}} \left[\sum_{t=1}^{|\tau|} \nabla_{\theta} \mathcal{H}^{\times}(\pi_{E}(\tau_{t}) | \pi_{\theta}(\tau_{t})) \right].$$

[88] provides a nice summarization of the related work on teacher and student distillations. While it is feasible to combine both distillation approaches [81], we observe that more recent work focuses on student distillation, which is empirically shown to encourage explorations on more states compared with teacher distillation, especially when the teacher policy is deterministic.

In general, there are two approaches of distilling the knowledge of teacher policies to a student: (1) including the per-time step supervise-loss with cross-entropy between the teachers and students distributions over actions [89], [90]; and (2) maximizing the probability that the teacher policy will visit trajectories generated by the student , i.e. $\max_{\theta} P(\tau \sim \pi_E | \tau \sim \pi_{\theta})$ [91], [92]. One example of approach (1) is the *Actor-mimic* algorithm [89]. This algorithm distills the knowledge of expert agents into the student by minimizing the cross entropy between the student policy π_{θ} and each teacher policy π_{E_i} over actions:

$$\mathcal{L}^{i}(\theta) = \sum_{a \in \mathcal{A}_{E_{i}}} \pi_{E_{i}}(a|s) \log_{\pi_{\theta}}(a|s).$$

where each teacher agent is learned using DQN network and its policy is therefore transformed from the Boltzmann distributions over the Q-function output:

$$\pi_{E_i}(a|s) = \frac{e^{\tau^{-1}Q_{E_i}(s,a)}}{\sum_{a' \in \mathcal{A}_{E_i}} e^{\tau^{-1}Q_{E_i}(s,a')}}.$$

An instantiation of approach (2) is the *Distral* algorithm [91], where a *centroid* policy π_{θ} is trained based on K teacher policies, with each teacher policy learned in a source MPD $\mathcal{M}_i = \{\mathcal{S}_i, \mathcal{A}_i, \mathcal{T}_i, \gamma, \mathcal{R}_i)\}$, in the hope that knowledge in

each teacher π_{E_i} can be distilled to the centroid and get transferred to student policies. It assumes that both the transition dynamics \mathcal{T}_i and reward distributions \mathcal{R}_i are different across source MDPs. A distilled policy (student) is learned to perform well in different domains by maximizing $\max_{\theta} \sum_{i=1}^K J(\pi_{\theta}, \pi_{E_i})$, where $J(\pi_{\theta}, \pi_{E_i}) =$

$$\sum_{t} \mathbb{E}_{(s_t, a_t) \sim \pi_{\theta}} \left[\sum_{t \geq 0} \gamma^t \left(r_i(a_t, s_t) + \frac{\alpha}{\beta} \log \pi_{\theta}(a_t | s_t) - \frac{1}{\beta} \log(\pi_{E_i}(a_t | s_t)) \right) \right],$$

in which both $\log \pi_{\theta}(a_t|s_t)$ and π_{θ} are used as augmented rewards, therefore, the above objective can optimized by *Reward Shaping* (Section 4.1). In effect, the $\log \pi_{\theta}(a_t|s_t)$ term guides the learning policy π_{θ} to generated actions more likely to be sampled by the teacher policy, whereas the entropy term $-log(\pi_{E_i}(a_t|s_t)$ serves as a bonus reward for exploration.

A similar approach is proposed by [90] which only uses the cross-entropy between teacher and student policy $\lambda \mathcal{H}(\pi_E(a_t|s_t)||\pi_\theta(a_t|s_t))$ to reshape rewards. Moreover, they adopted a dynamically fading coefficient to alleviate the effect of augmented reward, so that the student policy becomes independent of the teachers after certain optimization iterations.

4.3.2 Transfer via Policy Reuse

In addition to policy distillation, there are policy transfer approaches that take a different perspective, by *directly* reusing policies from source tasks to build the target policy.

The notion of *Policy Reuse* is mentioned by [93]. They proposed a way of directly reusing expert policies based on a probability distribution P, where the probability of each policy to be used during training is related to the expected performance gain of that policy in the target domain, denoted as W_i :

$$P(\pi_{E_i}) = \frac{\exp(tW_i)}{\sum_{j=0}^{K} \exp(tW_j)},$$

where t is a dynamic temperature parameter increases over time. Under a Q-learning framework, the Q-function of their target policy is learned in an iterative scheme: during every learning episode, W_i is evaluated for each expert policy π_{E_i} , and W_0 is obtained for the learning policy, from which a re-using probability P is derived. Next, a behavior policy is sampled from this probability P. If an expert is sampled as the behavior policy, the Q-function of the learning policy is updated by following the behavior policy in an ϵ -greedy fashion. Otherwise, if the learning policy itself is selected as

the behavior policy, then a fully greedy Q-learning update is performed. After each training episode, both W_i and the temperature t for calculating the re-using probability is updated accordingly. One limitation of this approach is that the W_i , i.e. the expected return of each expert policy on the target task, needs to be evaluated frequently. The authors of this work implemented their algorithm in a tabular case, making the scalability issue unresolved.

More recent work by [94] extended the *Policy Improvement* theorem [95] from one to multiple policies, which is named as *Generalized Policy Improvement*. We refer its main theorem as follows:

Theorem. (Generalized Policy Improvement (GPI))

Let $\pi_1, \pi_2, \ldots, \pi_n$ be n decision policies and let $\hat{Q}^{\pi_1}, \hat{Q}^{\pi_2}, \ldots, \hat{Q}^{\pi_n}$ be the approximations of their action-value functions, s.t: $\left|Q^{\pi_i}(s,a) - \hat{Q}^{\pi_i}(s,a)\right| \leq \epsilon \ \forall s \in \mathcal{S}, a \in \mathcal{A}$, and $i \in \{1, 2, \ldots, n\}$.

A, and
$$i \in \{1, 2, \dots, n\}$$
.

Define $\pi(s) = \underset{i}{\operatorname{arg max}} \max_{i} \hat{Q}^{\pi_{i}}(s, a)$, then:
$$Q^{\pi}(s, a) \geq \max_{i} Q^{\pi_{i}}(s, a) - \frac{2}{1 - \gamma} \epsilon$$

for any $s \in \mathcal{S}$ and $a \in \mathcal{A}$, where Q^{π} is the action-value function of π .

Based on this theorem, a policy improvement approach can be naturally derived by greedily choosing the action which renders the highest Q value among all policies for a given state. Another work along this line is [94], in which expert policy $\pi_{E_i}, i \in K$ is also trained on a different source domain \mathcal{M}_i with reward function \mathcal{R}_i , which means that $Q^\pi_{\mathcal{M}_0}(s,a) \neq Q^\pi_{\mathcal{M}_i}(s,a)$. To efficiently evaluate the Q-functions of different source policies in the target MDP, they utilize a neural network to first learn a disentangled representation $\psi(s,a)$ over the states and actions that is generalized across multiple tasks, and then learn a task (reward) mapper \mathbf{w}_i :

$$Q_i^{\pi}(s, a) = \boldsymbol{\psi}(s, a)^T \mathbf{w}_i.$$

[94] proved that the loss of GPI is bounded by the difference between source tasks and target tasks. In addition to policyreuse, their approach involves learning a shared representation $\psi(s,a)$, which is also a form of transfer knowledge and will be elaborated more in Section 4.6.1.

In general, both [93] and GPI [94] are approaches of reusing policies from source tasks directly to update the target policy, without implicit *policy distillation*. Both of them rely on estimating the performance of source policies on the target MDP to effectively update the target policy. [93] evaluates the *episodic return* of each source policy on the target MDP, while the later leverage the deep neural network to approximate its Q-function in a more efficient scheme.

4.4 Inter-Task Mapping

In this section, we review TL approaches that learn mapping functions between source and target tasks to assist knowledge transfer. Research in this domain can be analyzed from two perspectives: (1) which domain does the mapping function apply to, and (2) how the mapped representation is utilized. Most work discussed in this section shares a common assumption [50], [96]:

Assumption. (Existence of Mapping) A one-to-one mapping exist between the source and the target MDP.

Earlier work along this line requires *provided mapping functions* [50], [97]. One examples is [50] which assume that each target state (action) has a unique correspondence in the source MDP, and two mapping functions X_S, X_A are provided, such that $X_S(\mathcal{S}_t) \to \mathcal{S}_s, X_A(\mathcal{A}_t) \to \mathcal{A}_s$. Based X_S and X_A , a mapping function over Q-values $M(Q_s) \to Q_t$ can be learned. Another work is done by [97] which transfers *advice* as knowledge between source and target agents. In their settings, the advice comes from a human expert who manually generates the mapping function over Q-values in the source task, and transfer it to the learning policy for the new task. This *advice* encourages the learning agent to prefer certain good actions over the others, which equivalently provides a relative ranking of actions in the new task.

More later research tackles the inter-task mapping problem by automatically learning a mapping function [98]-[100]. Most work learn a mapping function over the state space or a subset of the state space. In their work, state representations are usually divided into agent-specific and task-specific representations, denoted as s_{agent} and s_{env} , respectively. In [98] and [99], the mapping function is learned on the agent-specific sub state, and the mapped representation is applied to reshape the immediate reward. For [98], the invariant feature space mapped from s_{agent} can be applied across agents who have distinct action space but share some morphological similarity. Specifically, they assume that both agents have been trained on the same proxy task, based on which the mapping function is learned. The mapping function is learned using a encoder-decoder neural network structure [101] in order to reserve as much information about the source domain as possible. While transferring knowledge from source agent to the target agent on a new task, the environment reward is augmented with an shaped reward term to encourage the target agent to imitate the source agent on the embedded feature space:

$$r'(s,\cdot) = \alpha ||f(s_{agent}^S; \theta_f) - g(s_{agent}^T; \theta_g)||,$$

where $f(s_{agent}^S)$ is the agent-specific state in the source domain, and $g(s_{agent}^T)$ is for the target domain.

[100] applied the Unsupervised Manifold Alignment (UMA) approach [102] to automatically learn the *state mapping* between tasks. They collect trajectories from both the source and the target task to learn a mapping between states. While applying policy gradient learning, trajectories from \mathcal{M}_t are first mapped back to the source: $\mathcal{T}_t \to \mathcal{T}_s$, then an expert policy in the source domain is applied to each initial state of those trajectories to generate near-optimal trajectories $\widetilde{\mathcal{T}}_s$, which are further mapped to the target domain: $\widetilde{\mathcal{T}}_s \to \widetilde{\mathcal{T}}_t$. The deviation between $\widetilde{\mathcal{T}}_t$ and \mathcal{T}_t are used as objective loss to improve the target policy. Similar ideas of using UMA to assist transfer by inter-task mapping can also be found in [103] and [104].

Another work by [96] proposes autonomous inter-task mapping over the *transition dynamics* space: $S \times A \times S$. Their work assumes that the source and target domains are different in terms of the transition space dimensionality, which without losing generality, are denoted as d_0 and

Citation	Transfer Approach	MDP Difference	RL framework	Metrics
[86]	distillation	\mathcal{S}, \mathcal{A}	DQN	ap
[87]	distillation	\mathcal{S}, \mathcal{A}	DQN	ap, ps
[89]	distillation	\mathcal{S}, \mathcal{A}	Soft Q-learning	ap, ar, ps
[91]	distillation	\mathcal{S}, \mathcal{A}	A3C	ap, pe, tt
[93]	reuse	\mathcal{R}	Tabular Q-learning	ap
[94]	reuse	\mathcal{R}	DQN	ap, ar

TABLE 3: A comparison of policy transfer approaches.

 d_1 , with $d_0 < d_1$. Their mapping framework involves a two-stage mapping process, based on a combination of sparse coding [105] and sparse Gaussian processes. The first stage is dimensional mapping, in which the transition triplets $\langle s_0, a_0, s'_0 \rangle$ of the task with lower dimensionality d_0 are sparse coded to a higher dimension, with the number of bases d_i equal to the higher dimension of the other task d_1 . Then the next stage further utilizes sparse coding to map both task transitions to a even higher space Z. Given the feature representation in Z with higher dimensionality, similarity measure can be applied to find a correspondence between the source and target task triplets. Triplet pairs with the highest similarity in this feature space Z are used to learn a mapping function \mathcal{X} : $\langle s_t, a_t, s_t' \rangle = \mathcal{X}(\langle s_s, a_s, s_s' \rangle)$, where $< s_s, a_t, s_t' >$ and $< s_t, a_s, s_s' >$ are the transition triplet pair in the source and target task after sparse projection. Sparse Pseudo-Inputs Gaussian Processes [106] are adopted to efficiently learning this mapping function \mathcal{X} . After the transition mapping, states sampled from the expert policy in the source domain can be leveraged to render beneficial states in the target domain, which assists the target agent learning with a better initialization performance. A similar idea of mapping transition dynamics can be found in [107], which however, requires stronger assumption on the similarity of transition probability and state representations between the source and the target task.

To summarize, inter-task mapping assumes the existence of one-to-one mapping between the source and target. The mapped knowledge can be (subset of) state space [98], [99], Q function [50], or (representation of) the transition tuple [96]. Besides directly applicable in the target task [96], the mapped representation can also be used as an augmented shaping reward [98], [99] or as a loss objective to minimize [100] in order to guide the agent learning in the target domain.

4.5 Reusing Representations

TL techniques discussed in this section apply to a problem setting in which there is no need to learn an explicit mapping between tasks. Instead, representations are either directly re-usable, or there exist task-invariant feature spaces so that knowledge can be transferred between tasks on that universal feature space.

A representative work is [108] which proposed the *progressive neural network* structure to enable transfer across multi-tasks in a progressive way. A progressive network is composed of multiple *columns*, where each column is a neural network for training one specific task. It starts with one single column for training the first task, and then the number of columns increases with the number of new tasks. While training on a new task neuron weights on the previous columns are frozen, and representations from those

frozen tasks are applied to the new column via a collateral connection to help train the new task. This process can be mathematically generalized to K tasks:

$$h_i^{(k)} = f\Big(W_i^{(k)}h_{i-1}^{(k)} + \sum_{j < k} U_i^{(k:j)}h_{i-1}^{(j)}\Big).$$

where $h_i^{(k)}$ is the i-th hidden layer for task (column) k, $W_i^{(k)}$ is the according weight matrix, and $U_i^{(k:j)}$ are the lateral connections from layer i-1 of previous tasks to the current layer of task k.

Although *progressive network* can be effective for small scale multi-task transfer, it comes with a cost of giant network structure, as the network grows along with new coming tasks. A later framework called *PathNet* is proposed by [109] which alleviates this issue by using a network with a fixed size. *PathNet* contains *pathways*, which are subsets of neurons whose weights contain the knowledge of previous tasks and are frozen during the training on new tasks. The population of *pathway* is evolved using a tournament selection genetic algorithm [110].

Another approach of reusing representations for TL is modular networks [111]–[113]. Especially, [111] decomposes the policy network into a task-specific module and agent-specific module, assuming that observation space can be disentangled in the same way. Their central idea is that the task-specific module can be applied to different agents performing the same module, while the agent-specific module can suit one task across different agents. Denoting a policy π performed by any agent (robot) r over task k as a function ϕ over observations o, it can be decomposed into two submodules g_k and f_r :

$$\pi(o) = \phi(o_{env}, o_{agent}) = f_r(g_k(o_{env}), o_{agent})$$

where f_r is the agent-specific module while g_k is the task-specific module.

[113] is another model-based approach which learns a *dynamics* module to map state observation s to a latent-representation z. Accordingly, the transition probability is modeled on the latent space instead of the original observation space: $\hat{z}_{t+1} = f_{for}(z, a; \theta_{for})$. Next, a *reward* module learns the value-function as well as the policy from the latent space z using an actor-critic framework. One potential benefit of this latent representation is that knowledge can be transferred across tasks which have different rewards but share the same transition dynamics, in which case the *dynamics* module can be directly applied to the target task.

4.6 Learning Disentangled Representations

Most work mentioned in Section 4.4 and 4.5 assumes that the state space, action space, or even reward distribution

Citation	Algorithm	MDP Difference	Mapping Function	Usage of Mapping
[50]	SARSA	$S_t \neq S_t$,	$M(Q_s) \to Q_t$	Q value reuse
		$A_s \neq A_t$		
[97]	Q-learning	$A_s \neq A_t$,	$M(Q_s) \rightarrow advice$	relative Q ranking
		$\mathcal{R}_s \neq \mathcal{R}_t$		
[98]	no constraint	$S_s eq S_t$	$M(s_{agent}) \rightarrow r'$	reward shaping
[99]	$SARSA(\lambda)$	$S_s \neq S_t$,	$M(s_{agent}) \rightarrow r'$	reward shaping
		$\mathcal{R}_s eq \mathcal{R}_t$		
[100]	Fitted Value Iter-	$S_s \neq S_t$	$M(s_s) \rightarrow s_t$	penalty loss on state de-
	ation			viation from expert pol-
				icy
[107]	Fitted Q Iteration	$S_s \times A_s \neq S_t \times$	$ M((s_s, a_s, s'_s) \to (s_t, a_t, s'_t)) $	reduce random explo-
		A_t		ration
[96]	no constraint	$S_s \times A_s \neq S_t \times$	$M((s_s, a_s, s_s') \rightarrow$	reduce random explo-
		\mathcal{A}_t	$M((s_s, a_s, s'_s) \to (s_t, a_t, s'_t))$	ration

TABLE 4: A comparison of inter-task mapping approaches.

space can be disentangled into independent, orthogonal subdomains, while how to learn such disentangled representation is not their focus. In contrast, methods discussed in this section shed light on learning a disentangled representation directly. Specifically, in this section we focus on TL approaches that are derived from two techniques: successor representation (SR) and universal value function approximating (UVFA), both of which are considered to provide affirmative theoretical support for TL in the RL domain. At the end of this section, we discuss some future extensions of SR and UVFA which might serve as a more general TL framework.

4.6.1 Successor Representations

Successor Representations (SR) is an approach to decouple the state features of an MDP from its reward distributions. It allows knowledge transfer across multiple MDPs: $\mathcal{M} = \{\mathcal{M}_1, \mathcal{M}_2, \dots, \mathcal{M}_K\}$, so long as the only difference is their reward distributions: $\mathcal{R}_i \neq \mathcal{R}_j$. SR was originally derived from neuroscience, until [114] proposed to leverage it as a generalization mechanism for state representations in the RL domain.

Different from the v-value or Q-value which describes states as dependent on the reward distribution of the MDP, SR features a state based on the *occupancy measure* of its *successor* states. More concretely, the occupancy measure is the unnormalized distribution of states or state-action pairs that an agent will encounter when following policy π in the MDP [30]. Specifically, SR decomposes the value-function of any policy into two independent components, ψ and R:

$$V^{\pi}(s) = \sum_{s'} \psi(s, s') \mathbf{w}(s'),$$

where ψ is the SR which describes any state s as the occupancy measure of the future occurred states when following π :

$$\psi(s, s') = \mathbb{E}_{\pi}[\sum_{i=t}^{\infty} \gamma^{i-t} \mathbb{1}[S_i = s'] | S_t = s]$$

with $\mathbb{1}[S=s']=1$ as an indicator function. ψ is *reward-agnostic* and only depends on two components: (1) the transition dynamics of the MPD; and (2) the sampling policy π . $\mathbf{w}(s')$ is a reward mapping function which maps states to scalar rewards.

The *successor* nature of SR makes it learnable using any Temporal Difference learning algorithms [115]. [114] proved

the feasibility of learning such representation in a tabular case, in which the state transitions can be described using a matrix. SR was later extended by [94] from three perspectives: (i) the feature domain of SR is extended from states to state-action pairs; (ii) deep neural networks are used as function approximators to represent the SR $\psi^{\pi}(s,a)$ and the *reward mapper* w; (iii) Generalized policy improvement (GPI) algorithm is introduced to accelerate policy transfer for multi-tasks facilitated by the SR framework. These extensions, however, are built upon a stronger assumption about the MDP:

Assumption. (*Linearity of reward distributions*) the reward functions of all tasks can be computed as a linear combination of a fixed set of features:

$$r(s, a, s') = \phi(s, a, s')^{\mathsf{T}} \mathbf{w}.$$
 (4)

 $\phi(s,a,s') \in \mathbf{R}^d$ can be interpreted as a latent representation of the state transition, while $\mathbf{w} \in \mathbf{R}^d$ is the task-specific reward mapper. Based on this assumption, SR can be decoupled from the rewards when evaluating the Q-function of any policy π in a task \mathcal{M}_i with a reward function \mathcal{R}_i :

$$Q_i^{\pi}(s, a) = \mathbb{E}^{\pi}[r_{t+1}^i + \gamma r_{t+2}^i + \dots | S_t = s, A_t = a]$$

$$= \mathbb{E}^{\pi}[\phi_{t+1}^{\top} \mathbf{w}_i + \gamma \phi_{t+2}^{\top} \mathbf{w}_i + \dots | S_t = s, A_t = a]$$

$$= \boldsymbol{\psi}^{\pi}(s, a)^{\top} \mathbf{w}_i. \tag{5}$$

It turns out that $\psi^{\pi}(s,a)$ satisfies the Bellman Equation, and therefore can be learned using any conventional RL method, by treating the latent representation $\phi(s,a,s')$ as the immediate reward:

$$\psi^{\pi}(s, a) = \phi_{t+1} + \gamma \mathbf{E}^{\pi} [\psi^{\pi}(S_{t+1}, \pi(S_{t+1})) | S_t = s, A_t = a].$$

The advantage of SR is that, when the knowledge of $\psi^{\pi}(s,a)$ in \mathcal{M}_s is observed, one can quickly get the performance evaluation of the same policy in \mathcal{M}_t by replacing \mathbf{w}_s with \mathbf{w}_t : $Q^{\pi}_{\mathcal{M}_t} = \psi^{\pi}(s,a)\mathbf{w}_t$. The reward mapper \mathbf{w}_i for a specific \mathcal{M}_i given $\psi^{\pi}(s,a)$ can be approximated by supervise-learning: $r^i_{t+1} = r^i(s_t,a_t,s_{t+1}) \approx \phi^{\top}_{t+1}\widetilde{\mathbf{w}}_i$. Once the Q function of policy π in a new MDP is estimated, GPI can take over to learn a new policy which performs no worse than π in the new MDP. More details about GPI have been elaborated in Section 4.3.2.

Similar ideas of learning SR as a TD algorithm on a latent representation $\phi(s,a,s')$ can also be found in earlier

work [116], [117]. Specifically, [116] requires a milder assumption than Equation (4): Instead of requiring a linearly decoupled rewards, the latent space $\phi(s,a,s')$ is learned in an encoder-decoder structure to ensure that the information loss is minimized when mapping states to the latent space. This structure, therefore, comes with an extra cost of learning a decoder f_d to reconstruct the state: $f_d(\phi(s_t)) \approx s_t$.

An upcoming question for SR is: Is there a way to evade the linearity assumption about reward functions and still able to learn the SR without extra modular cost? An extended work of SR [118] answers this question affirmatively, by proving that the reward functions do not necessarily have to follow the linear structure, at a cost of a looser performance lower-bound while applying the GPI approach (Section (4.3.2).

Rather than learning a reward-agnostic latent feature $\phi(s,a,s') \in \mathbf{R}^d$ for multiple tasks, [118] aims to learn a matrix $\phi(s,a,s') \in \mathbf{R}^{D \times d}$ to interpret the basis functions of the latent space instead, where D is the number of seen tasks. Assuming k out of D tasks are linearly independent, this matrix forms k basis functions for the latent space. Therefore, for any unseen task \mathcal{M}_i , its latent features can be built as a linear combination of these basis functions, so as its reward functions $r_i(s,a,s')$. Based on the idea of learning basisfunctions for the task latent space, they propose that learning $\phi(s,a,s')$ can be approximated as learning $\mathbf{r}(s,a,s')$ directly, where $\mathbf{r}(s,a,s') \in \mathbf{R}^D$ is a vector of reward functions for each seen task:

$$\mathbf{r}(s, a, s') = [r_1(s, a, s'); r_2(s, a, s'), \dots, r_D(s, a, s')].$$

Accordingly, learning $\psi(s, a)$ for any policy π_i in \mathcal{M}_i becomes equivalent to learning a collection of Q-functions:

$$\widetilde{\psi}^{\pi_i}(s, a) = \left[Q_1^{\pi_i}(s, a), Q_2^{\pi_i}(s, a), \dots, Q_D^{\pi_i}(s, a) \right].$$

A similar idea of using reward functions as features to represent unseen tasks is also proposed by [119], which however assumes the ψ and ${\bf w}$ as observable quantities from the environment.

4.6.2 Universal Function Approximation

Universal Function Approximation (UVFA) is an alternative approach of learning disentangled state representations [120]. Same as SR, UVFA allows transfer learning for multiple tasks where asks differ only by their reward functions (goals). Different from SR which focuses on learning a reward-agnostic state representation, UVFA aims to find a function approximator that is generalized for both states and goals. The UVFA framework is built on one assumption:

Assumption. (Goals as States) Task goals can be defined in terms of states, e.g. given the state space S and the goal space G, it satisfies that $G \subseteq S$.

One instantiation of this assumption can be an agent exploring different locations in a maze environment, where the goals are described as certain locations inside the maze. Based on this assumption, a UVFA module can be decoupled into a state embedding and a goal embedding by leveraging the idea of matrix factorization [121]. Learning such decoupled representations follows a two-stage procedure: In the first stage, a matrix is built, with each row representing a state $s \in \mathcal{S}$ and each column representing a goal $g \in \mathcal{G}$, while

each entry in the matrix is the reward for being at state s in a task of goal g. Low-rank factorization is performed on the matrix to find a target state embedding $\mathcal{S} \to \hat{\phi}(s) \in \mathbf{R}^n$ and a target goal embedding $\mathcal{G} \to \hat{\psi}(g) \in \mathbf{R}^n$, so that a simple operation, e.g. the dot product of both targets is able to reconstruct the original matrix representation. In the second stage, multi-variate regression is performed to learn two embedding networks $\phi(s)$ and $\psi(g)$.

One beneficial property of the UVFA framework for transfer learning resides in its transferrable embedding $\phi(s)$ across tasks which only differ by goals. Another merit of UVFA is its ability of continual learning when the set of goals keep expanding over time [122]. On the hand, one of its challenges is that matrix factorization into low-rank space itself is time-consuming as a subtask. The feasibility of performing matrix factorization on complex environments with large $|\mathcal{S}|$ is a practical concern. Even with learned embedding networks, a third stage of fine-tuning these networks via end-to-end training is still necessary. Authors of the paper refer to the OptSpac tool for matrix factorization [123].

An inspiration from UVFA is that the state embedding $\phi(s)$ and goal embedding $\psi(s)$ can be symmetric, or even come from the same feature space. One way to intuitively interpret this symmetry is to consider the maze example again, where the UVFA embeddings are learned as the distance between the current state(location) s and the goal state(location) s. This symmetric architecture encourages transfer knowledge between $\phi(s)$ and $\psi(s)$. Moreover, it draws a connection to an extended work of SR [118], in which a set of independent rewards (tasks) themselves can be used as features for state representations.

An extension of both UVFA and SR is called Universal Successor Feature Approximator (USFA), which is proposed by [124]. Following the same linearity assumption about rewards as in Equation (4), USFA is proposed as a function over state, action, and a policy embedding z:

$$\phi(s, a, z) : \mathcal{S} \times \mathcal{A} \times \mathbf{R}^k \to \mathbf{R}^d,$$

where z is the output of a policy-encoding mapping $z=e(\pi)$: $\mathcal{S}\times\mathcal{A}\to\mathbf{R}^k$. Based on USFA, the Q-function of any policy π for a task specified by \mathbf{w} can be formularized as the product of a reward-agnostic Universal Successor Feature (USF) ψ and a reward mapper \mathbf{w} :

$$Q(s, a, \mathbf{w}, z) = \boldsymbol{\psi}(s, a, z)^{\top} \mathbf{w}.$$

The above Q-function representation is distinct from Equation (5), as the $\psi(s,a,z)$ is generalized over multiple policies, with each denoted by z. Facilitated by the disentangled rewards and policy generalization, they further introduce a generalized TD-error as a function over tasks w and policy z, which allows them to approximate the Q-function of any policy on any task using a TD-algorithm.

4.6.3 Summary and Discussion

In general, learning disentangled representation is a promising field to facilitate transfer learning in many ways, and work along this line usually shares a common assumption space. Most of them assume that tasks are different only in terms of their reward distributions, while sharing the same states (or actions or transitions) probabilities.

Stronger assumptions include (i) decoupled dynamics (or rewards [94] or policies [124]) from the Q-function representations, and (ii) the feasibility of defining tasks in terms of states [124]. Based on those assumptions, approaches such as TD-algorithms [118] or matrix-factorization [120] become applicable to learn such disentangled representations. To further exploit the effectiveness of disentangled structure, generalization approaches which allows changing dynamics or state distributions is a future work which is worth more attention in this domain.

As challenging ongoing research, there are unresolved questions in learning disentangled representation. One is how to handle drastic changes of reward functions between tasks. As discussed in [125], good policies in one MDP may perform poorly in another, due to the fact that beneficial states or actions in \mathcal{M}_s may become detrimental in \mathcal{M}_t with totally different reward functions. Especially, as discussed in the GPI work [94], the performance lower-bound is determined by the reward function discrepancy while transferring knowledge across different tasks. Learning a set of basis functions [118] to represent unseen tasks (reward functions), or decoupling policies from Q function representation [124] may serve as a good start to address this issue, as they proposes a generalized latent space, from which different tasks (reward functions) can be interpreted. The limitation of their work is that it is not clear how many and what kind of sub-tasks need to be learned, in order to make the latent space effective to interpret unseen tasks.

Another question is *how to generalize the representation* framework to allow transferring across tasks with different dynamics (or state-action spaces). A learned SR might not be transferrable to an MDP with different transition dynamics, as the distribution of occupancy measure for successor states no longer holds even when following the same policy. Potential solutions may include model-based approaches that approximate the dynamics directly, or training a latent representation space for states using multiple tasks with different dynamics for better generalization [126]. Alternatively, TL mechanisms from the supervised learning domain, such as utilizing importance sampling [127] to compensate for the prior distribution changes [10], might also shed lights onto this question.

5 APPLICATIONS

In this section, we summarize successful applications of RL with TL techniques.

Robotics learning is an important topic in both machine learning and the RL domain. [128] provides a comprehensive survey of applying RL techniques to robotics learning. Under the RL framework, a classical TL approach for facilitating robotics learning is robotics learning from demonstrations, where expert demonstrations from humans or other robots are leveraged to teach the learning robot. A survey of robotic learning from demonstrations provides a nice summarization of approaches in this topic [129].

Later on, a scheme of *collaborative robotic training* has emerged, along with a survey paper [130]. By collaborative training, knowledge from different robots is transferred by sharing their policies and episodic demonstrations with each other. A recent instantiation of this approach can be found

in [131]. Their approach can be considered as a policy transfer across multiple robot agents under the DQN framework, by sharing their demonstrations in a pool and performing policy updates asynchronously.

Recent work of reinforcement robotics learning with TL approaches emphasize more on the ability of fast and robust adaptation to unseen tasks. A typical approach to achieve this property is designing and selecting multiple source tasks for robust training so that a generalized policy trained on those source tasks can be quickly transferred to target tasks. Examples include the EPOPT approach proposed by [132], which is a hybrid work of policy transfer via source domain ensemble and learning from limited demonstrations for fast adaptation to the target task. Another application can be found in [133], which provides robust agent policies to handles dynamic environments, trained by a large number of synthetic demonstrations from a simulator. Another idea for fast adaptation is to learn latent representations from source task observations which are generally applicable to the target task. An example of this scenario is training robots using simulated 2D image inputs and applying the robot in real 3D environments. Work along this line includes [134] which learns the latent representation using 3D CAD models, and [135], [136] which adopt the Generative-Adversarial Network. Another example is DARLA [137], which a zero-shot transfer approach that learns disentangled representations for its robot agents to be robust against domain shifts.

Game Playing is one of the most adopted testbeds for TL and RL algorithms. Both the complexity and diversity of games for evaluating TL approaches have evolved over the recent decades, ranging from classical testbeds such as grid-world games, to more complex game settings such as online-strategy games or video games with pixel GRB inputs. A representative TL application in game playing is AlphaGo, which is an online chessboard game agent learned using both TL and RL approaches [68]. AlphaGo is first trained offline using expert demonstrations and then learns to optimize its policy using Monte-Carlo Tree Search. Its successor, AlphaGo Master [138], even beat the world No.1 ranked player at that time.

Besides online chessboard games, TL approaches have also performed well in playing video games. Current video game platforms are *MineCraft*, *Atari*, and *Starcraft*. Especially, [139] designed new RL tasks under the *MineCraft* platform for a better comparison of different RL algorithms. A survey of AI for real-time strategy (RTS) games on the *Starcraft* platform can be found in [140], with a dataset available from [141]. [142] provides a comprehensive survey on DL applications in video game playing, which also covers TL and RL strategies from certain perspectives. A large portion of TL approaches reviewed in this survey have been applied to the *Atari* [143] and other game above-mentioned platforms. Especially, OpenAI trained an *Dota2* agent which surpasses human experts [144]. Game applications of TL approaches mentioned in this survey are summarized in Table 6.

Natural Language Processing (NLP) research has evolved rapidly along with the advancement of DL and RL. There is an increasing trend of addressing NLP problems by leveraging RL techniques. Applications of RL on NLP range widely, from *Question Answering (QA)* [145], *Dialogue*

Citation	Representations Format	Assumptions	MDP Difference	Learner	Metrics
[108]	lateral connections to previously learned network modules		\mathcal{S}, \mathcal{A}	A3C	ap, ps
[109]	selected neural paths		\mathcal{S}, \mathcal{A}	A3C	ap
[111]	task(agent)-specific net- work module	disentangled state representation	\mathcal{S}, \mathcal{A}	Policy Gradient	ap
[113]	dynamic transitions module learned on latent representations of the state space		\mathcal{S}, \mathcal{A}	A3C	ap, pe
[94]	SF	reward function can be linearly decoupled	$\mathcal R$	DQN	ap, ar
[116]	encoder-decoder learned SF		$\mathcal R$	DQN	pe, ps
[118]	encoder-decoder learned SF	rewards can be represented by set of basis functions	\mathcal{R}	$Q(\lambda)$	ap, pe
[120]	matrix-factorized UF	goals are defined in terms of states	$\mathcal R$	Tabular Q-learning	ap, pe, ps
[124]	policy-encoded UF	reward function can be linearly decoupled;	\mathcal{R}	ϵ -greedyQ-learning	ap, pe

TABLE 5: A comparison of TL approaches that transfer representations.

systems [146], Machine Translation [147], to an integration of NLP and Computer Vision tasks, such as Visual Question Answering (VQA) [148], Image Caption [149], etc. Many of these NLP applications have implicitly applied TL approaches, including learning from demonstrations, policy transfer, or reward shaping, to better tailor these RL techniques as NLP solutions which were previously dominated by supervise-learning counterparts [150]. Examples include applying expert demonstration to build RL solutions to Spoken Dialogue Systems [151], VQA [148]; or building shaped rewards for Sequence Generation [152], Spoken Dialogue Systems [64],QA [65], [153], and Image Caption [149], or transferring policies for Structured Prediction [154] and VQA [155], etc. We provide information of above-mentioned applications in Table 7.

Health Informatics is another domain that has benefited from the advanced development of RL. RL techniques have shown to help in many healthcare tasks, including dynamic treatment regimes [156], [157], automatic medical diagnosis [158], [159], health resource scheduling [160], [161], and drug discovery and development, [162], [163] etc. An overview of recent achievements of RL techniques in health informatics domains is provided by [164]. Despite the emergence of abundant studies of applying (deep) RL to address healthcare problems, a limited number of them have utilized TL approaches, although we do observe some applications which have leveraged prior knowledge to help the RL procedure: [165] utilized Q-learning for drug delivery individualization. They integrated the prior knowledge of the dose-response characteristics into their Q-learning framework and leveraged this prior knowledge to avoid unnecessary exploration. Some work has considered reusing representations for speeding up decision making [166], [167]. [166] proposed to highlight both individual variability and common policy model structure for individual HIV treatment. [167] applied a DDQN framework for prescribing effective HIV treatments, where they learn a latent representation to estimate the uncertainty when transferring pertained policy for unseen task instances. [168] considered the potential of applying human-involved interactive RL training for health informatics. We consider TL in RL a promising integration to be applied in the

health informatics domain to further improve the learning speed and sample efficiency, especially given the difficulty of accessing large amounts of clinical data.

Others: Besides the above-mentioned topics, RL has also been utilized in many real-life applications. For example, Transportation Systems domain has adopted RL for addressing traffic congestion issues with better traffic signal scheduling and transportation resource allocation [8], [9], [169], [170]. A review of application of RL algorithms on traffic signal controls is provided by [171]. RL and Deep RL are also shown to be effective solutions to problems in Finance, including portfolio management [172], [173], asset allocation [174], trading optimization [175], etc. *Electricity Systems*, especially intelligent electricity networks, have been also built based on RL techniques for power-delivery decisions [176], [177] and active resource management [178]. Please refer to [7] for a survey of RL models for electric power system applications. Although few of them have explicitly leveraged TL in RL settings, we believe that given a plethora of theoretical and algorithm breakthroughs in TL and DRL research, it is promising to embrace a hybrid framework of TL and DRL techniques for further accelerating the development of these domains.

6 FUTURE PERSPECTIVES

In this section, we propose some future research directions for TL in the RL domain:

Modeling Transferability: A key question for TL is, whether or to what extent, can the knowledge of solving one task help in solving another? Answering this question helps in many stages of achieving automatic TL, including the source task selection, the mapping function design, disentangling representations, avoiding negative transfer, and etc.

In this survey, we propose a theoretical framework to define the transferability of two tasks, as shown in Figure 3: For two tasks \mathcal{M}_i and \mathcal{M}_j , the knowledge of solving \mathcal{M}_i is transferrable to solve \mathcal{M}_j , if there exist:

Game	Citation	TL Approach	Note
Atari, 3D Maze	[50]	Transferrable	Progressive network
		representation	
Atari, Mujoco	[76]	LFD	POfD
Atari	[71]	LFD	
Go	[68]	LFD	AlphaGo
Keepaway	[50]	Mapping	
RoboCup	[97]	Mapping	
Atari	[86]	Policy Transfer	Distillation
Atari	[87]	Policy Transfer	
Atari	[89]	Policy Transfer	
3D Maze	[91]	Policy Transfer	
Dota2	[144]	Reward Shaping	

TABLE 6: Applications of TL approaches in Game Playing.

Citation	Application	TL Approach
[151]	Spoken Dialogue System	LFD
[148]	VQA	LFD
[152]	Sequence Generation	LFD, Reward Shaping
[65]	QA	Reward Shaping
[153]	QA	LFD, Reward Shaping
[154]	Structured Prediction	Policy Transfer
[155]	Grounded Dialog Generation	Policy Distillation
[149]	Image Caption	Reward Shaping

TABLE 7: Applications of TL approaches in Natural Language Processing.

• two *invertible* mapping functions g_i and g_j , which map the state representation of the two MDPs to a common latent space \mathcal{Z}_S :

$$g_i: \mathcal{S}_i \to \mathcal{Z}_S, g_s^{-1}: \mathcal{Z} \to \mathcal{S}_i$$

 $g_i: \mathcal{S}_i \to \mathcal{Z}_S, g_s^{-1}: \mathcal{Z} \to \mathcal{S}_i$

• two *invertible* mapping functions f_i and f_j , which map the action representation of the two MDPs to a common latent space \mathcal{Z}_A :

$$g_i: \mathcal{A}_i \to \mathcal{Z}_A, g_s^{-1}: \mathcal{Z}_A \to \mathcal{A}_i$$

 $g_i: \mathcal{A}_i \to \mathcal{Z}_A, g_s^{-1}: \mathcal{Z}_A \to \mathcal{A}_i$

• a set of policies Π , $|\Pi| \ge 1$ and a constant ϵ , such that $\forall \pi \in \Pi, \pi : \mathcal{Z}_S \times \mathcal{Z}_A \to [0, 1]$, π is a *good* policy for both \mathcal{M}_i and \mathcal{M}_j :

$$\begin{aligned} \left| V_{\mathcal{M}_i}^{\pi} - V_{\mathcal{M}_i}^* \right| &\leq \epsilon \\ \left| V_{\mathcal{M}_i}^{\pi} - V_{\mathcal{M}_i}^* \right| &\leq \epsilon \end{aligned}$$

Evaluating Transferability: Evaluation metrics have been proposed to evaluate TL approaches from different but complementary perspectives, although no single metric can summarize the efficacy of a TL approach. Designing a set of generalized, novel metrics is beneficial for the development of TL in DRL domain. In addition to the current benchmark sets such OpenAI gym² which is designed purely for evaluating RL approaches, a unified benchmark to evaluate the TL performance is also worth research and engineering efforts.

Framework-agnostic Transfer: Most contemporary TL approaches only suit certain RL frameworks. For example, some TL methods are applicable to RL algorithms designed for discrete-action space (such as DQfD), while others may suit a continuous action space. Also, TL approaches may be limited

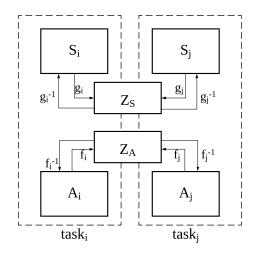


Fig. 3: Transferability of two tasks.

to only an on-policy / off-policy setting. The fundamental reason of these framework-dependent TL methods derives from the diversified development of RL algorithms itself. We expect that a more unified RL framework future would in turn accelerate the standardization of TL development in this field.

Interpretability: Deep learning and end-to-end systems have made network representation to be black-box, making it difficult to explain and debug the model's representations or decisions. As a result, there have been efforts in defining and evaluating interpretable approaches in the supervise-learning domain [179]–[181]. The merits of Interpretability are manifolds, including generating disentangled representations, building explainable models, facilitating human-computer-interactions, etc. At the meantime, interpretable TL approaches for the RL domain, especially with explainable representations or policy decisions, can also be beneficial to

many applied fields, such as *robotics* and *finance*. Moreover, *interpretability* can also help in avoiding catastrophic decision-making for tasks such as auto-driving or healthcare decisions. Although there has emerged work towards explainable TL approaches for RL tasks [182], [183], there is no clear definition of interpretable TL in the RL domain, nor a systematic process to assess the interpretability of different TL approaches. We believe that the standardization of interpretable TL for RL will be a topic that is worth more attention and effort in the near future.

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