Abstract

The past few years have seen rapid progress in combining reinforcement learning (RL) with deep learning. Various breakthroughs ranging from games to robotics have spurred the interest in designing sophisticated RL algorithms and systems. However, the prevailing workflow in RL is to learn tabula rasa, which may incur computational inefficiency. This precludes continuous deployment of RL algorithms and potentially excludes researchers without large-scale computing resources. In many other areas of machine learning, the pretraining paradigm has shown to be effective in acquiring transferable knowledge, which can be utilized for a variety of downstream tasks. Recently, we saw a surge of interest in Pretraining for Deep RL with promising results. However, much of the research has been based on different experimental settings. Due to the nature of RL, pretraining in this field is faced with unique challenges and hence requires new design principles. In this survey, we seek to systematically review existing works in pretraining for deep reinforcement learning, provide a taxonomy of these methods, discuss each sub-field, and bring attention to open problems and future directions.

1. Introduction

Reinforcement learning (RL) provides a general-purpose mathematical formalism for sequential decision-making (Sutton & Barto, 2018). By utilizing RL algorithms together with deep neural networks, various milestones in different domains have achieved superhuman performances via optimizing user-specified reward functions in a data-driven manner (Silver et al., 2016; Akkaya et al., 2019; Vinyals et al., 2019; Ye et al., 2020, 2020, 2022; Chen et al., 2021b). As such, we have seen a growing interest recently in this research direction.

However, while RL has been proven effective at solving well-specified tasks, the issue of sample efficiency (Jin et al., 2021) and generalization (Kirk et al., 2021) still hinder its application to real-world problems. In RL research, a standard paradigm is to let the agent learn from its own or others’ collected experience, usually on a single task, and to optimize neural networks tabula rasa with random initializations. For humans, in contrast, prior knowledge about the world contributes greatly to the decision-making process. If the task is related to previously seen tasks, humans tend to reuse what has been learned to quickly adapt to a new task, without learning from exhaustive
interactions from scratch. Therefore, as compared to humans, RL agents usually suffer from great data inefficiency (Kapturowski et al., 2022) and are prone to overfitting (Zhang et al., 2018).

Recent advances in other areas of machine learning, however, actively advocate for leveraging prior knowledge built from large-scale pretraining. By training on broad data at scale, large generic models, also known as *foundation models* (Bommasani et al., 2021), can quickly adapt to various downstream tasks. This pretrain-finetune paradigm has been proven effective in areas like computer vision (Chen et al., 2020; He et al., 2020; Grill et al., 2020) and natural language processing (Devlin et al., 2019; Brown et al., 2020). However, pretraining has not yet had a significant impact on the field of RL. Despite its promise, designing principles for large-scale RL pretraining faces challenges from many sources: 1) the diversity of domains and tasks; 2) the limited data sources; 3) the difficulty of fast adaptation to solve downstream tasks. These factors stem from the nature of RL and are inevitably necessary to be considered.

This survey aims to present a bird’s-eye view of current research on *Pretraining in Deep RL*. Principled pretraining in RL has a variety of potential benefits. First of all, the substantial computational cost incurred by RL training remains a hurdle for industrial applications. For example, replicating the results of AlphaStar (Vinyals et al., 2019) approximately costs millions of dollars (Agarwal et al., 2022). Pretraining can ameliorate this issue, either with pretrained world models (Sekar et al., 2020) or pretrained representations (Schwarzer et al., 2021b), by enabling quick adaptation to solve tasks in zero or few-shot manner. Besides, RL is notoriously task- and domain-specific. It has already been shown that pretraining with massive task-agnostic data can enhance these kinds of generalizations (Lee et al., 2022). Finally, we believe that pretraining with proper architectures can unlock the power of scaling laws (Kaplan et al., 2020), as shown by recent success in games (Schwarzer et al., 2021b; Lee et al., 2022). By scaling up general-purpose models with increased computation, we are able to further achieve superhuman results, as taught in the “bitter lesson” (Sutton, 2019).

Pretraining in deep RL has undergone several breakthroughs in recent years. *Naive pretraining with expert demonstrations*, using supervised learning to predict the actions taken by experts, has been exhibited with the famed AlphaGo (Silver et al., 2016). To pursue large-scale pretraining with less supervision, the field of *unsupervised RL* has been growing rapidly in recent years (Burda et al., 2019a; Laskin et al., 2021), which allows the agent to learn from interacting with the environment in the absence of reward signals. In accordance with recent advances in offline RL (Levine,
et al., 2020), researchers further consider how to leverage unlabeled and sub-optimal offline data for pretraining (Stooke et al., 2021; Schwarzer et al., 2021b), which we term offline pretraining. The offline paradigm with task-irrelevant data further paves the way towards generalist pretraining, where diverse datasets from different tasks and modalities as well as general-purpose models with great scaling properties are combined to build generalist models (Reed et al., 2022; Lee et al., 2022).

Pretraining has the potential to play a big role for RL and this survey could serve as a starting point for those interested in this direction. In this paper, we seek to provide a systematic review of existing works in pretraining for deep reinforcement learning. To the best of our knowledge, it is one of the pioneering efforts to systematically study pretraining in deep RL.

Following the development trend of pretraining in RL, we organize the paper as follows. After going through the preliminaries of reinforcement learning and pretraining (Section 2), we start with online pretraining in which an agent learns from interacting with the environment without reward signals (Section 3). And then, we consider offline pretraining, the scenario where unlabeled training data is collected once with any policy (Section 4). In Section 5, we discuss recent advances in developing generalist agents for a variety of orthogonal tasks. We further discuss how to adapt to downstream RL tasks (Section 6). Finally, we conclude this survey together with a few prospects (Section 7).

### 2. Preliminaries

#### 2.1 Reinforcement learning

Reinforcement learning considers the problem of finding a policy that interacts with the environment under uncertainty to maximize its collected reward. Mathematically, this problem can be formulated...
via a Markov Decision Process (MDP) defined by tuple \((S, A, T, \rho_0, r, \gamma)\), with a state space \(S\), an action space \(A\), a state transition distribution \(T : S \times A \times S \rightarrow [0, 1]\), an initial state distribution \(\rho_0 : S \rightarrow [0, 1]\), a reward function \(r : S \times A \rightarrow \mathbb{R}\), and a discount factor \(\gamma \in (0, 1)\). The objective is to find such a policy \(\pi_{\theta}(a|s)\) parameterized by \(\theta\) that maximizes

\[
J(\pi_{\theta}) = \mathbb{E}_{\pi_{\theta}, T, \rho_0} \left[ \sum_{t=0}^{\infty} \gamma^t r(s_t, a_t) \right],
\]

known as the discounted returns. The notation used in the paper is summarized in Table 1.

### 2.2 Pretraining

Pretraining aims at obtaining transferable knowledge from large-scale training data to facilitate downstream tasks. In the context of RL, transferable knowledge typically includes good representations that facilitate the agent to perceive the world (i.e., a better state space) and reusable skills from which the agent can quickly build complex behaviors given task descriptions (i.e., a better action space). Training data can be one bottleneck for effective RL pretraining. Unlike what we have witnessed in fields like computer vision and natural language processing where a wealth of unlabeled data can be collected with minimal supervision, RL usually requires highly task-specific reward design, which hinders scaling up pretraining for large-scale applications.

Therefore, the focus of this survey is unsupervised pretraining, in which task-specific rewards are unavailable during pretraining but it is still allowed to learn from online interaction, unlabeled logged data, or task-irrelevant data from other modalities. We omit supervised pretraining given that with task-specific rewards this scenario roughly degenerates to existing RL settings (Levine et al., 2020). Figure 1 demonstrates an overview of the pretraining and adaptation process.

The objective is to acquire useful prior knowledge in various forms like good visual representations, exploratory policies \(\pi_{\theta}(a|s)\), latent-conditioned policies \(\pi(a|s, z)\), or simply logged datasets. Depending on what data is available during pretraining, it requires different considerations to obtain useful knowledge (Section 3-5) and adapt it accordingly to downstream tasks (Section 6).

### 3. Online Pretraining

Most of the previous successes in RL have been achieved given dense and well-designed reward functions. Despite its primacy in providing excel performances for a specific task, the traditional RL paradigm faces two critical challenges when scaling it up to large-scale pretraining. Firstly, it is notoriously easy for an RL agent to overfit (Zhang et al., 2018). As a result, a pretrained agent trained with sophisticated task rewards can hardly generalize to unseen task specifications. Furthermore, it remains a practical challenge to design reward functions which is usually costly and requires expert knowledge.

Online pretraining without these reward signals can potentially be a good solution to learning generic skills and eliminate the supervision requirement. Online pretraining aims at acquiring prior knowledge by interacting with the environment in the absence of human supervision. During the pretraining phase, the agent is allowed to interact with the environment for a long period without access to extrinsic rewards. When the environment is accessible, playing with it facilitates skill learning that will be useful later when a task is assigned to the agent. This solution, also known as
unsupervised RL, has been actively studied in recent years (Burda et al., 2019a; Srinivas & Abbeel, 2021).

To encourage the agent to build its own knowledge without any supervision, we need principled mechanisms to provide the agent with intrinsic drives. Psychologists found that babies can discover both the tasks to be learned and the solution to those tasks through interacting with the environment (Smith & Gasser, 2005). With experiences accumulated, they are capable of more difficult tasks later on. This motivates a wealth of research that studies how to build self-taught agents with intrinsic rewards (Schmidhuber, 1991; Singh et al., 2004; Oudeyer et al., 2007). Intrinsic rewards, in contrast to task-specifying extrinsic rewards, refer to general learning signals that encourage the agent either to collect diverse experiences or to develop useful skills. It has been shown that pretraining an agent with intrinsic rewards and standard RL algorithms can lead to fast adaptation once the downstream task is given (Laskin et al., 2021).

Based on how to design intrinsic rewards, we classify existing approaches of unsupervised RL into three categories: curiosity-driven exploration, skill discovery, and maximal data coverage. Table 2 presents a categorization of representative online pretraining algorithms together with their used intrinsic rewards.

### 3.1 Curiosity-driven Exploration

In the psychology of motivation, curiosity represents motivation to reduce uncertainty about the world (Silvia, 2012). Inspired by this line of psychological theory, similar ideas have been studied to build curiosity-driven approaches for online pretraining. Curiosity-driven approaches seek to explore interesting states that can possibly bring knowledge about the environment. Intuitively, if the agent falls short of accurately predicting the environment, it gains knowledge by interacting and then reducing this part of the uncertainty. The defining characteristic of a curiosity-driven agent

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1. This taxonomy of unsupervised RL was originally proposed by Srinivas and Abbeel (2021).
is how to compute the degree of curiosity to these interesting states, which directly serves as the intrinsic reward for learning. A concrete example is ICM (Pathak et al., 2017), which applies the intrinsic reward proportional to the prediction error as shown in Figure 2:

\[ r_t \propto \| f(\phi(s_t), a_t) - \phi(s_{t+1}) \|_2^2, \]

where \( f \) and \( \phi \) represent the learned forward dynamics model and feature encoder, respectively.

To measure curiosity, a broad class of approaches (Pathak et al., 2017; Haber et al., 2018) leverages this kind of learned dynamics models to predict future states in an auxiliary feature space. There are mainly two kinds of estimation: prediction error and prediction uncertainty. Despite that these dynamics-based approaches perform quite well across common scenarios, they usually suffer from action-dependent noisy TVs (Burda et al., 2019a), which will be discussed later in Section 3.1.1. This deficiency encourages the following work to design dynamics-free curiosity estimation (Burda et al., 2019b) and more sophisticated uncertainty estimation methods (Pathak et al., 2019; Sekar et al., 2020).

Another important design choice is associated with the feature encoder \( \phi \), especially for high-dimensional observations. A proper feature encoder can make the prediction task more tractable and filter out irrelevant aspects so that the agent can only focus on the informative ones. Early studies (Stadie et al., 2015; Burda et al., 2019a) leverage auto-encoding embeddings to recover the original high-dimensional inputs, but the induced feature space is usually too informative about irrelevant details and hence susceptible to noise. To address this issue, Pathak et al. (2017) utilize an inverse dynamics model for feature encoding to make sure that the agent is unaffected by nuisance factors in the environment. The proposed ICM shows impressive zero-shot performance in playing video games. Burda et al. (2019b) further relax the design burden by simply replacing the feature model with a fixed randomly initialized neural network, which is proven effective by a following large-scale empirical study (Burda et al., 2019a). Despite that random feature encoders are sufficient for good performance at training, learned features (e.g., based on inverse dynamics) generalize better (Burda et al., 2019a). Inspired by recent advances in representation learning, Du et al. (2021)
\[ r_t = \log q(z | h_{t+1}) - \log p(z) \]

Figure 3: The process of computing intrinsic rewards using skill discovery approaches.

directly link curiosity and representation learning loss by formulating a minimax game between a
generic representation learning algorithm and a reinforcement learning policy.

3.1.1 CHALLENGES & FUTURE DIRECTIONS

This kind of approach has several deficiencies. One of the most important issues is how to distin-
guish \textit{epistemic} and \textit{aleatoric} uncertainty. Epistemic uncertainty refers to uncertainty caused by a
lack of knowledge. Aleatoric uncertainty, in contrast, refers to the variability in the outcome due to
inherently random effects. A concrete phenomenon in RL is the noisy TV problem (Mavor-Parker
et al., 2022), which refers to the cases where the agent gets trapped by its curiosity in highly stochastic
environments. To mitigate this issue, some work attempts to use intrinsic rewards proportional
to a reduction in uncertainty (Houthooft et al., 2016; Pathak et al., 2019). However, tractable episco-
temic uncertainty estimation in high dimension remains challenging (Hüllermeier & Waegeman,
2021) due to its sensitivity to imperfect data.

Another issue with the above approaches is that they only receive retrospective signals after
the agent has achieved epistemic uncertainty, which might cause inefficiency in exploration. Based
on this intuition, Sekar et al. (2020) design a model-based method that can prospectively look for
uncertainty in the environment.

3.2 Skill Discovery

Apart from curiosity-driven approaches that tackle unsupervised RL in a model-based perspective,
one can also consider model-free learning of primitive skills\(^2\) that can be composed to solve down-
stream tasks. This kind of approach is usually referred to as skill discovery approach. The main
intuition behind this is that the learned skill should control which states the agent visits, which can
be seen as a notion of empowerment.

Generally speaking, the objective for skill discovery can be formalized as maximizing the mu-
tual information (MI) between skill latent variable \(z\) and state \(s\):

\[
I(s; z) = H(z) - H(z | s) = H(s) - H(s | z),
\]

where we define \textit{skills} or \textit{options} as the policies conditioned on \(z\). There are two components for a
skill discovery agent to determine: 1) a skill distribution \(p(z)\); 2) a skill policy \(\pi(a|s, z)\). Before
each episode, skill latent \(z\) is sampled from distribution \(p(z)\), followed by skill \(\pi(a|s, z)\) to interact

\(^2\) In this work, we use \textit{skill}, \textit{option}, and \textit{behavior prior} interchangeably.
with the environment. Learning skills that maximize MI is a challenging optimization problem, upon which a variety of approaches sharing the same spirit have been applied.

Among the existing MI-based skill discovery methods, the majority (Gregor et al., 2016; Eysenbach et al., 2019; Hansen et al., 2020) apply the former form of Equation 1 with the following variational lower bound (Agakov, 2004):

\[ I(s; z) = \mathbb{E}_{s, z \sim p(s, z)}[\log p(z | s)] - \mathbb{E}_{z \sim p(z)}[\log p(z)] \geq \mathbb{E}_{s, z \sim p(s, z)}[\log q(z | s)] - \mathbb{E}_{z \sim p(z)}[\log p(z)]. \]

In this case, a parametric model \( q(z | s) \) is trained together with other variables to estimate the conditional distribution \( p(z | s) \). Maximizing \( H(z) \) can be achieved by sampling \( z \) from a learned distribution (Gregor et al., 2016) or directly from a fixed uniform distribution (Eysenbach et al., 2019). As shown in Figure 3, the intrinsic reward is given by \( r_t = \log q(z | s_t) - \log p(z) \), upon which one can apply standard RL algorithms to learn skills.

Another line of research (Sharma et al., 2020; Campos et al., 2020; Liu & Abbeel, 2021a; Laskin et al., 2022) considers the latter form and similarly derives a lower bound:

\[ I(s; z) = \mathbb{E}_{s, z \sim p(s, z)}[\log p(s | z)] - \mathbb{E}_{s \sim p(s)}[\log p(s)] \geq \mathbb{E}_{s, z \sim p(s, z)}[\log q(s | z)] - \mathbb{E}_{s \sim p(s)}[\log p(s)]. \]

In this formulation, maximizing the state entropy \( H(s) \) encourages exploration while minimizing the conditional entropy results in directed behaviors. The difficulty lies in the density estimation of \( s \), especially for high-dimensional state spaces. A common practice is to maximize \( H(s) \) via maximum entropy estimation (Hazan et al., 2019; Lee et al., 2019; Liu & Abbeel, 2021b), which will be elaborated more in Section 3.3.

Although different work uses slightly different approaches to optimize Equation 1, it could be more important to decide other design factors when using skill discovery for online pretraining. For instance, while most studies consider the episodic setting, some efforts have been made to extend MI-based skill discovery to non-episodic settings (Xu et al., 2020; Lu et al., 2021b). It is also promising to consider a curriculum with an increasing number of skills to learn (Achiam et al., 2018). Several other factors are also worth mentioning, such as whether skill latent \( z \) is discrete (Achiam et al., 2018) or continuous (Warde-Farley et al., 2019), whether the reward signals are dense (Eysenbach et al., 2019) or sparse (Gregor et al., 2016), and whether it works for image-based observations (Warde-Farley et al., 2019).

Skill discovery can be also reinterpreted as goal-conditioned policy learning, where \( z \) as self-generated and abstract goal is sampled from a distribution instead of provided by the task. One can also consider generating concrete goals in a self-supervised manner (Warde-Farley et al., 2019; Pong et al., 2020) and derive a goal-conditioned reward function similarly from MI maximization. DISCERN (Warde-Farley et al., 2019) designs a non-parametric approach for goal sampling, maintaining a buffer of past observations that drifts as the agent collects new experiences. Skew-Fit (Pong et al., 2020) instead learns a maximum entropy goal distribution by increasing the entropy of a generative model in an iterative manner. Choi et al. (2021) provide a more formal connection mainly from the perspective of goal-conditioned RL. We refer the interested reader to Colas et al. (2022) for further discussion.
3.2.1 Challenges & Future Directions

A major issue for MI-based skill discovery approaches is that the objective does not necessarily lead to strong state coverage as one can maximize $I(s; z)$ even with the smallest state variations (Campos et al., 2020; Park et al., 2022). This lack of coverage can greatly limit their applicability to downstream tasks with complex environments (Campos et al., 2020). To resolve this issue, some existing work explicitly uses $x$-$y$ coordinates as features to enforce state coverage induced by skills (Eysenbach et al., 2019; Sharma et al., 2020). It is also explored to separate the learning process to first maximize $H(s)$ via maximum entropy estimation, followed by behavior learning (Campos et al., 2020; Liu & Abbeel, 2021a).

Moreover, it is empirically shown that skill discovery methods underperform other kinds of online pretraining methods, which may be due to restricted skill spaces (Laskin et al., 2021). This calls attention to dissecting what skills are learned. In order to live up to their full potential, the discovered skills must strike a balance between generality (i.e., the applicability to a large variety of downstream tasks) and specificity (i.e., the quality of being useful to induce specific behaviors) (Gehring et al., 2021). It is also desired to avoid learning trivial skills (Sharma et al., 2020; Baumli et al., 2021).

3.3 Data Coverage Maximization

Previously we have discussed how to obtain knowledge or skills, measured by the agent’s own capability, from unsupervised interaction. Albeit indirectly related to the agent’s ability, data diversity induced by online pretraining plays an essential role in deciding how well the agent obtains prior knowledge. In the field of supervised learning, recent advances have shown that diverse data can enhance out-of-distribution generalization (Hendrycks et al., 2020b) and robustness (Hendrycks et al., 2020a). Another supporting evidence is that most of the famed datasets are large and diverse (Deng et al., 2009; Wang et al., 2019). Motivated by the above considerations, it is desired to use data coverage maximization, usually measured by state visitation, as an objective to stimulate unsupervised learning.

3.3.1 Count-Based Exploration

The first category of data coverage maximization is count-based exploration. Count-based exploration methods directly use visit counts to guide the agent towards underexplored states (Bellemare et al., 2016; Ostrovski et al., 2017). For tabular MDPs, Model-based Interval Estimation with Exploration Bonuses (Strehl & Littman, 2008) provably turn state-action $N(s, a)$ counts into an exploration bonus reward:

$$r_t \propto N(s_t, a_t)^{-1/2}. \tag{2}$$

Built on Equation 2, a series of work has studied how to tractably generalize count bonuses to high-dimensional state spaces (Bellemare et al., 2016; Ostrovski et al., 2017; Tang et al., 2017). To approximate these counts in high dimensions, Bellemare et al. (2016) introduce pseudo-counts derived from a density model. Specifically, the pseudo-count is defined as:

$$\tilde{N}(s) = \frac{\rho_t(s) (1 - \rho_t'(s))}{\rho_t'(s) - \rho_t(s)},$$
where \( \rho \) is a density model over state space \( S \), \( \rho_t(s) \) is the density assigned to \( s \) after training on a sequence of states \( s_1, \ldots, s_t \), and \( \rho'_t(s) \) is the density of \( s \) if \( \rho \) were to be trained on \( s \) one additional time. Based on similar ideas, it has been shown that a better density model (Ostrovski et al., 2017) or a hash function (Tang et al., 2017; Rashid et al., 2020) for computing state statistics can further improve performance. Besides, a self-supervised inverse dynamics model as discussed in Section 3.1 can also be used to bias the count-based bonuses towards what the agent can control (Badia et al., 2020).

### 3.3.2 Entropy Maximization

To encourage novel state visitation, an alternative objective is to directly maximize the entropy of state visitation distribution \( d_\pi \) induced by policy \( \pi(\theta) \):

\[
\pi^* \in \arg \max_{\pi \in \Pi} H(d_\pi),
\]

where \( H(\cdot) \) can be Shannon entropy (Hazan et al., 2019; Lee et al., 2019; Seo et al., 2021), Rényi entropy (Zhang et al., 2021b), or geometry-aware entropy (Guo et al., 2021). The state distribution \( d_\pi \) can either be a discounted distribution (Hazan et al., 2019), a marginal distribution (Lee et al., 2019), or a stationary distribution (Tarbouriech & Lazaric, 2019).

Albeit compelling, the objective relies on maximizing state entropy, which is notoriously hard to estimate and optimize. Hazan et al. (2019) contribute a provably efficient algorithm in the tabular setting using the conditional gradient method (Frank & Wolfe, 1956) to avoid direct optimization. Lee et al. (2019) propose a similar approach that can be viewed from the perspective of state marginal matching between the state distribution and a given target distribution (e.g., a uniform distribution). Both Hazan et al. (2019) and Lee et al. (2019) propose to learn a mixture of policies that maximizes the induced state entropy in an iterative manner. While impressive, these parametric approaches struggle to scale up to high dimensional spaces. To address this issue, Mutti et al. (2020) instead optimize a non-parametric, particle-based estimate of state distribution entropy (Kontoyiannis et al., 1998), but restrict its use to state-based tasks.

For unsupervised online pretraining with visual observations, entropy maximization becomes more tricky as exploration is now inextricably intertwined with representation learning. This leads to a chicken-and-egg problem (Yarats et al., 2021; Tam et al., 2022), where learning useful representations requires diverse data, while effective exploration can only be achieved with good representations. Based on particle-based entropy estimators, several approaches successfully apply entropy maximization in image-based tasks with self-supervised representations learned by inverse dynamics prediction (Seo et al., 2021), contrastive learning (Liu & Abbeel, 2021b; Yarats et al., 2021), or the information bottleneck (Tao et al., 2020).

### 3.3.3 Challenges & Future Directions

Although count-based approaches are shown effective for exploration, it has been shown in previous work (Ecoffet et al., 2021) that they usually suffer from detachment, in which the agent loses track of interesting areas to explore, and derailment, in which the exploratory mechanism prevents it from returning to previously visited states. Count-based approaches also tend to be short-sighted, driving the agent to get stuck in local minima (Burda et al., 2019b).
When applying state entropy maximization approaches for pretraining, it is worth pointing out that many of them aim at maximizing the entropy of all states visited during the process, and hence the final policy is not necessarily exploratory (Lee et al., 2019). It has also been shown theoretically that the class of Markovian policies is insufficient for the maximum state entropy objective, while non-Markovian policies are essential to guarantee good exploration.

Instead of learning an exploratory policy, another line of research considers collecting unlabeled records as a prerequisite for offline RL (Yarats et al., 2022; Lambert et al., 2022), which is an interesting direction for understanding and utilizing task-agnostic agents.

4. Offline Pretraining

Despite its attractive effectiveness of learning without human supervision, online pretraining is still limited for large-scale applications. Eventually, it is difficult to reconcile online interaction with the need to train on large and diverse datasets (Levine, 2021). To address this issue, it is desired to decouple data collection and pretraining and directly leverage historical data collected from other agents or humans.

A feasible solution is offline RL (Lange et al., 2012; Levine et al., 2020), which has been gaining attention recently. Offline RL aims to obtain a reward-maximizing policy purely from offline data. A fundamental challenge of offline RL is the distributional shift, which refers to the distribution discrepancy between training data and those seen during testing. Existing offline RL approaches focus on how to address this challenge when using function approximation. For instance, policy constraint approaches (Kumar et al., 2019; Siegel et al., 2020) explicitly require the learned policy to avoid taking unseen actions in the dataset. Value regularization methods (Kumar et al., 2020) alleviate the overestimation problem of value functions by fitting them to some forms of lower bounds. However, it remains under-explored whether policies trained offline can generalize to new contexts unseen in the offline dataset (Kirk et al., 2021).

Another scenario is offline-to-online RL (Nair et al., 2020; Lu et al., 2022; Lee et al., 2022; Kostrikov et al., 2022), where offline RL is used for pretraining, followed by online finetuning. It has been shown in this scenario that offline RL can accelerate online RL (Nair et al., 2020). However, both offline RL and offline-to-online RL require the offline experience to be annotated with rewards, which are challenging to provide for large real-world datasets (Pertsch et al., 2021a).

A compelling alternative direction for leveraging offline data is to sidestep policy learning, but instead learn prior knowledge that is beneficial for downstream tasks in terms of convergence speed.
or final performances. What is more intriguing, if our model were able to utilize data without human supervision, it could potentially benefit from web-scale data for decision-making. We refer to this setting as offline pretraining, where the agent can extract important information (e.g., good representations and behavior priors) from offline data. In Table 3, we categorize existing offline pretraining approaches as well as summarize each approach’s key properties.

4.1 Skill Extraction

Learning useful behaviors from offline data has a long history (Pomerleau, 1988; Argall et al., 2009). When the offline data comes from expert demonstrations, it is straightforward to pretrain policies via imitation learning (Silver et al., 2016; Rajeswaran et al., 2018; Gupta et al., 2020), which is often used in real-world applications like robotic manipulation (Zhu et al., 2018; Zhang et al., 2018) and self-driving (Codevilla et al., 2019). However, imitation learning approaches often assume that the training data contains complete solutions. They therefore usually fall short of obtaining good policies when demonstrations are collected from a series of sources.

An alternative solution is to learn useful behavior priors from offline data (Lynch et al., 2020; Shankar & Gupta, 2020; Chebotar et al., 2021), similar to what we have discussed in Section 3.2. Compared with its online counterpart, offline skill extraction assumes a fixed set of trajectories. These approaches learn a spectrum of behavior policies conditioned on latent $z$, which provide a more compact action space for learning high-level policies that can quickly adapt to downstream tasks. Specifically, temporal skill extraction (Yang et al., 2022) for few-shot imitation (Ajay et al., 2021) and RL (Ajay et al., 2021; Pertsch et al., 2021a, 2021b) considers how to distill offline trajectories into primitive policies $\pi(a|s, z)$, where $z \in Z$ denotes a skill latent learned via unsupervised learning. By leveraging stochastic latent variable models, we aim at learning a skill latent $z_i \in Z$ for a sequence of state-action pairs $\{s_t, a_t, \ldots, s_{t+H-1}, a_{t+H-1}\}$, where $H$ is a fixed horizon or a variable one (Kipf et al., 2019; Shankar et al., 2020). For example, Ajay et al. (2021) propose the following auto-encoding objective to learn primitive skills:

$$\min_{\theta, \phi, \omega} J(\theta, \phi, \omega) = \mathbb{E}_{\tau \sim D, z \sim q_{\phi}(z|\tau)} \left[ - \sum_{t=0}^{H-1} \log \pi_{\theta}(a_t | s_t, z) \right]$$

s.t. $\mathbb{E}_{\tau \sim D} \left[ D_{KL} (q_{\phi}(z | \tau) \| \rho_{\omega}(z | s_0)) \right] \leq \epsilon_{KL},$

where $q_{\phi}(z | \tau)$ encodes the trajectory $\tau$ into skill latent $z$ and skill policy $\pi(a|s, z)$ serves as a decoder to translate skill latent $z$ into action sequences. To transfer skills into downstream tasks, it is feasible to learn a hierarchical policy that generates high-level behaviors with $\pi(z | s)$ trained on downstream tasks (Pertsch et al., 2021a), which will be elaborated in Section 6.2.

Various latent variable models have been used for pretraining behavior priors. For instance, variational auto-encoders (Kingma & Welling, 2014) are widely considered (Pertsch et al., 2021a; Lynch et al., 2020; Ajay et al., 2021). Following work (Singh et al., 2021; Florence et al., 2022) also explores normalizing flow (Dinh et al., 2017) and energy-based models (LeCun et al., 2006) to learn action priors.

The scenario of pretrained behavior priors also bears resemblance to few-shot imitation learning (Dance et al., 2021; Hakhamaneshi et al., 2022). However, for few-shot imitation learning, it is often assumed that expert data is collected from a single behavior policy. Furthermore, due to error accumulation (Ross et al., 2011), few-shot imitation learning is often limited to short-horizon
problems (Hakhamaneshi et al., 2022). In this regard, learning behavior priors from diverse and sub-optimal data appears to be a promising direction.

4.1.1 Challenges & Future Directions

Despite its potential to extract useful primitive skills, it is still challenging to pretrain on highly sub-optimal offline data containing random actions (Ajay et al., 2021). Besides, RL with learned skills does not usually generalize to downstream tasks efficiently, requiring millions of online interactions to converge (Hakhamaneshi et al., 2022). A possible solution is to combine with successor features (Barreto et al., 2017; Hansen et al., 2020) for fast task inference. However, strategies that directly use the pretrained policies for exploitation may result in sub-optimal solutions in such a scenario (Campos et al., 2021).

4.2 Representation Learning

While pretraining behavior priors focus on reducing the complexity of the action space, there exists another line of work that aims to pretrain good state representations from offline data to promote transfer. If the agent effectively reduces the representation gap between the learned state representations and the ground-truth endogenous states, it can better focus on factors that are essential for control. Table 4 compares different kinds of representation learning objectives in terms of sufficiency (i.e., whether the representations contain sufficient state information) and compactness (i.e., whether the representations discard irrelevant information).

| Type                  | Sufficiency | Compactness |
|-----------------------|-------------|-------------|
| Reconstruction        | ⭐⭐⭐         | ⭐           |
| Forward Pixel Prediction | ⭐⭐⭐         | ⭐           |
| Forward Dynamics Modeling | ⭐⭐         | ⭐⭐⭐⭐       |
| Inverse Dynamics Modeling | ⭐         | ⭐⭐⭐⭐⭐      |

Table 4: Comparison between different representation learning approaches.
approaches typically train an auto-encoder on image observations to learn a low-dimensional representation, using which a policy is learned subsequently. Approaches based on pixel prediction force the representations to contain sufficient information about future pixel observations. Despite these learned representations preserving sufficient information about the observation, it lacks compactness and does not guarantee to capture of useful information for the control task.

Instead of predicting the future, it is also beneficial to model the inverse dynamics of the system (Christiano et al., 2016; Pathak et al., 2017). Inverse dynamics modeling learns a representation that is predictive of the action taken between a pair of consecutive states. It has been shown that the learned representation can filter out all uncontrollable aspects of the observations (Efroni et al., 2021). However, it can also wrongly ignore controllable information and cause over-abstraction over the state space (Rakelly et al., 2021; Efroni et al., 2021).

With the rise of self-supervised learning developed for CV and NLP, a natural direction is to adapt these task-agnostic techniques to RL. For instance, a large body of works has explored contrastive learning (Gutmann & Hyvärinen, 2010) as an effective framework to learn good representations (Nachum et al., 2019; Laskin et al., 2020; Mazoure et al., 2020; Zhan et al., 2020). Contrastive learning typically uses the InfoNCE loss (Poole et al., 2019) to maximize mutual information between two variables:

\[
\mathcal{L}_{\text{InfoNCE}} = \mathbb{E} \left[ \log \frac{\exp(f(x_i, y_i))}{\frac{1}{K} \sum_{j=1}^{K} \exp(f(x_i, y_j))} \right],
\]

where \( f \) is a bilinear function \( f(x_i, y_i) = \phi(x_i)^T W \phi(y_i) \) with learned parameter \( W \in \mathbb{R}^{n \times n} \) and \( K \) is the number of negative samples. These approaches usually incorporate temporal information, aiming to distinguish between sequential and non-sequential states (Anand et al., 2019; Stooke et al., 2021). Following works (Schwarzer et al., 2021a, 2021b) further consider bootstrapped latent representations (Grill et al., 2020) that get rid of negative samples.

Aside from the above representation learning objectives, some other work considers imposing Lipschitz smoothness (Gelada et al., 2019; Zhang et al., 2021a), kinematic inseparability (Misra et al., 2020), or the Markov property (Allen et al., 2021). It has also been shown that a combined objective can also lead to better performance (Schwarzer et al., 2021b).

4.2.1 Challenges & Future Directions

While unsupervised representations have been shown to bring significant improvements to downstream tasks, the absence of reward signals typically leads the pretrained encoder to focus on task-irrelevant features instead of task-relevant ones in visually complex environments (Yamada et al., 2022). To alleviate this issue, one might incorporate additional inductive bias (Janny et al., 2022) or labeled data that are cheaper to obtain. We will discuss the latter solution in Section 5.

Another challenge for unsupervised representation learning is how to measure its effectiveness without access to downstream tasks. Such evaluation is beneficial because it can provide a proxy metric to predict performance and promote a deeper understanding of the semantic meanings of pretrained representations. To achieve this, it is desired to analyze these representations with probing techniques and determine which properties they encode. Although previous work has made efforts in this direction (Zhang et al., 2022a), it remains unclear what properties are most indispensable for pretrained representations.
5. Towards Generalist Agents with RL

So far we have discussed online and offline scenarios that are generally restricted to a single modality and single environment. Recently, there is a surge of interest in building a single *generalist model* (Reed et al., 2022; Lee et al., 2022; Fan et al., 2022) to handle tasks in different environments across different modalities. To enable the agent to learn from and adapt to various open-ended tasks, it is desired to leverage considerable prior knowledge in different forms such as visual perception and language understanding. Intuitively, the aim is to bridge the worlds of RL and other fields of machine learning, combining previous success together to build a large decision-making model capable of a diverse set of tasks. In this section, we look at various considerations for handling data and tasks from different modalities to acquire useful prior knowledge.

5.1 Visual Pretraining

Perception is an unavoidable prerequisite for real-world applications. With an increased number of image-based decision-making tasks, pretrained visual encoders that were exposed to a wide distribution of images can provide RL agents with robust and resilient representations as a basis to learn optimal policies.

The field of computer vision has seen tremendous progress in pretraining visual encoders from large-scale image datasets (Deng et al., 2009) and video corpora (Abu-El-Haija et al., 2016). Given that these data are cheap to access, several works have explored the use of pretrained visual encoders on large-scale image datasets as means to improve the generalization and sample efficiency of RL agents. Shah and Kumar (2021) equip standard deep RL algorithms with ResNet encoders pretrained on ImageNet and observe that the pretrained representations lead to impressive performances in Adroit (Rajeswaran et al., 2018) but struggle in the DeepMind control suite (Tassa et al., 2018) due to large domain gap. Parisi et al. (2022) further investigate various design choices including datasets, augmentations, and layers, and report positive results on all four considered control tasks. Träuble et al. (2022) conduct a large-scale study on how different properties of pretrained VAE-based embeddings affect out-of-distribution generalization, concluding that some of them (e.g., the GS metric (Dittadi et al., 2021)) can be good proxy metrics to predict generalization performance.

Instead of extracting visual information from static image datasets, another intriguing direction is to capture temporal relations from unlabeled videos. Sermanet et al. (2018) design a self-supervised approach to learning temporal variance and multi-view invariance on multi-view video data. Xiao et al. (2022) empirically find that, without exploiting temporal information, in-the-wild images collected from YouTube or Egocentric videos lead to better self-supervised representations for manipulation tasks that ImageNet images. Seo et al. (2022) introduce a two-phase learning framework, which first learns useful representations via generative pretraining on videos and then uses the pretrained model for learning action-conditional world models. Baker et al. (2022) successfully extract behavioral priors from internet-scale videos with an inverse dynamics model to uncover the underlying actions followed by behavior cloning, finding that the pretrained model exhibits impressive zero-shot capabilities and finetuning results for playing Minecraft. Zhang et al. (2022) also leverage inverse dynamics models to predict action labels from action-free videos, upon which a new contrastive learning framework is proposed to pretrain action-conditioned policies.
5.2 Natural Language Pretraining

Human beings are not only able to perceive the visual world through their eyes, but understand high-level natural language instructions and ground the rich knowledge from texts to complete tasks. In this vein, there has been a long history of how to connect language and actions (Kollar et al., 2010; Tellex et al., 2011). Especially due to the rapid development of large language models (LLMs) (Brown et al., 2020; Chowdhery et al., 2022) that exhibit great capability of encoding semantic knowledge, it appears to be a promising direction to leverage advanced LLMs as generic computation engines to facilitate decision making (Lu et al., 2021a).

5.2.1 LANGUAGE-CONDITIONED POLICY LEARNING

To extract and harness the knowledge of well-informed pretrained LLMs, a feasible solution is to condition the policies on text descriptions processed by LLMs. This kind of language-conditioned policy learning could be extremely useful for robotic tasks where high-level language instructions are available. For example, Ahn et al. (2022) use pretrained LLMs to split high-level instructions into sub-tasks via prompt engineering for grounding value functions in real-world robotic tasks. Huang et al. (2022b) further enable grounded closed-loop feedback generated by additional perception models as the source of corrections for LLMs’ predictions. Tam et al. (2022) instead consider effective exploration in 3D environments, showing that pretrained representations from vision-language models (Radford et al., 2021) form a semantically meaningful state space for curiosity-driven intrinsic rewards. Mahmoudieh et al. (2022) also connect reward specification to vision-language supervision, introducing a framework that leverages text descriptions and pixel observations to produce reward signals.

5.2.2 POLICY INITIALIZATION

Recent advances bridge the gap between reinforcement learning and sequential modeling (Chen et al., 2021a; Janner et al., 2021; Zheng et al., 2022; Furuta et al., 2022), opening up opportunities to borrow sequential models to RL tasks. Despite the clear distinction, pretrained LLMs could arguably provide reusable knowledge via weight initialization. Reid et al. (2022) investigate whether pretrained LLMs can provide good weight initialization for Transformer-based offline RL models, and conclude with very positive results. Li et al. (2022b) also demonstrate that pretrained LLMs can be used to initialize policies and facilitate behavior cloning as well as online reinforcement learning for embodied tasks. They also suggest using sequential input representations and finetuning the pretrained weights for better generalization.

5.3 Multi-task and Multi-modal Pretraining

With recent advances in building powerful sequence models to handle different modalities and tasks (Lu et al., 2019; Jaegle et al., 2022; Wang et al., 2022), the wave of using large general-purpose models (Bommasani et al., 2021) has been sweeping through the field of supervised learning. The key ingredient is Transformer (Vaswani et al., 2017), a highly capable neural architecture built on the self-attention mechanism (Bahdanau et al., 2015) that excels at capturing long-range dependencies in sequential data. Due to its strong generality where various tasks in different domains can be formulated as sequence modeling, Transformer is believed to be a unified architecture for developing foundation models (Bommasani et al., 2021).
Recently, Transformer-based architectures have also been extended to the field of offline RL (Chen et al., 2021a; Janner et al., 2021) and then online RL (Zheng et al., 2022), in which the agent is trained auto-regressively in a supervised manner via likelihood maximization. This opens up the possibility of replicating previous success achieved with Transformer in the field of supervised learning. Specifically, it is expected that by combining large-scale data, open-ended objectives, and Transformer-based architectures, we are ready to build general-purpose decision-making agents that are capable of various downstream tasks in different environments.

Pioneering work in this direction is Gato (Reed et al., 2022), a generalist agent trained on various tasks from control environments, vision datasets, and language datasets in a supervised manner. To handle multi-task and multi-modal data, Gato uses demonstrations as prompt sequences (Wei et al., 2022) at inference time. Lee et al. (2022) extend Decision Transformer (Chen et al., 2021a) to train a generalist agent called Multi-Game DT that can play 41 Atari games simultaneously. Both Gato and Multi-Game DT show impressive scaling law properties. Fan et al. (2022) make use of large-scale multi-modal data from YouTube videos, Wikipedia pages, and Reddit posts to train an agent able to solve various tasks in Minecraft. To provide dense reward signals, a pretrained vision-language model based on CLIP (Radford et al., 2021) is introduced as a proxy of human evaluation.

5.4 Challenges & Future Directions

In spite of some promising results, how generalist models benefit from multi-modal and multi-task data remains unclear. More specifically, these models might suffer from detrimental gradient interference (Yu et al., 2020) between modalities and tasks due to the incurred optimization challenges. To mitigate this issue, it is desired to incorporate more analysis tools for optimization landscapes (Goodfellow & Vinyals, 2015) and gradients (Yu et al., 2020) to tease out the precise principles.

Another compelling direction is to compose separate pretrained models (e.g., GPT-3 (Brown et al., 2020) and CLIP (Radford et al., 2021)) together. By leveraging expert knowledge from different models, this kind of framework can solve complex multi-modal tasks (Li et al., 2022a).

6. Task Adaptation

While pretraining on unsupervised experiences can result in rich transferable knowledge, it remains challenging to adapt the knowledge to downstream tasks in which reward signals are exposed. In this section, we discuss briefly various considerations for downstream task adaptation. We limit the scope to online adaptation, while adaptation with offline RL or imitation learning is also feasible (Yang & Nachum, 2021).

In online task adaptation, a pretrained model is given, which can be composed of various components such as policies and representations, together with a target MDP that can interact with. Given that pretraining could result in different forms of knowledge, it brings difficulties to designing principled adaptation techniques. Nevertheless, considerable efforts have been made to study this aspect.

6.1 Representation Transfer

In the field of supervised learning, recent advances (Devlin et al., 2019; He et al., 2020; Chen et al., 2020) have demonstrated that good representations can be pretrained on large-scale unlabeled
dataset, as evidenced by their impressive downstream performances. The most common practice is to freeze the weights of the pretrained feature encoder and train a randomly initialized task-specific network on top of that during adaptation. The success of this paradigm is essentially based on the promise that related tasks can usually be solved using similar representations.

For RL, it has been shown that directly reusing pretrained task-agnostic representations can significantly improve sample efficiency on downstream tasks. For instance, Schwarzer et al. (2021b) conduct experiments on the Atari 100K benchmark and find that frozen representations pretrained on exploratory offline data already form a basis of data-efficient RL. This success also extends to the cases where domain discrepancy exists between upstream and downstream tasks (Shah & Kumar, 2021; Parisi et al., 2022). However, the issue of negative transfer in the face of domain discrepancy might be exacerbated for RL due to its complexity (Shah & Kumar, 2021).

When adapting to tasks that have the same environment dynamics as that of the upstream task(s), successor features (Barreto et al., 2017) can be a powerful tool to aid task adaptation. The framework of successor features is based on the following decomposition of reward functions:

$$r(s, a, s') = \phi(s, a, s')^\top w,$$

where \(\phi(s, a, s') \in \mathbb{R}^d\) represents features of transition \((s, a, s')\) and \(w \in \mathbb{R}^d\) encodes reward-specifying weights. This leads to a representation of the value function that decouples the dynamics of the environment from the rewards:

$$Q^\pi(s, a) = \mathbb{E}_{s_1, a_1 = a} \left[ \sum_{i=t}^{\infty} \gamma^{i-t} \phi(s_{i+1}, a_{i+1}, s'_{i+1}) \right]^\top w = \psi^\pi(s, a)^\top w,$$

where we call \(\psi^\pi(s, a)\) the successor features of \((s, a)\) under \(\pi\). Intuitively, \(\psi^\pi\) summarizes the dynamics induced by \(\pi\) and has been studied within the framework of online pretraining (Hansen et al., 2020; Liu & Abbeel, 2021a) by combining with skill discovery approaches to implicitly learn controllable successor features \(\psi^\pi(s, a)\). Given a learned \(\psi^\pi(s, a)\), the problem of task adaptation reduces to a linear regression derived from Equation 3.

### 6.2 Policy Transfer

A compelling alternative for task adaptation is to transfer learned behaviors. As discussed in previous sections, existing work has explored how to pretrain primitive skills that can be reused to face new tasks or a single exploratory policy that facilitates exploration at the beginning of task adaptation. The differences in pretrained behaviors result in different adaptation strategies.

To achieve high rewards on the downstream task with skill-conditioned policy \(\pi(a|s, z)\), a straightforward strategy is to simply choose the skill \(z\) with the best outcome and further enhance it with finetuning. However, a single best-performing skill can not fulfill its potential. To better combine diverse skills for task solving, one can view them from the perspective of hierarchical RL (Barto & Mahadevan, 2003; Kulkarni et al., 2016). In hierarchical RL, the decision-making task is typically decomposed into a two-level hierarchy, where a meta-controller \(\pi(z|s)\) decides which low-level policy to use for task solving, depending on the current state. This hierarchical scheme is agnostic to how the low-level policies are learned. Therefore, it is sufficient to train a meta-controller on top of the discovered skills, which has been proven effective for few-shot adaptation (Hakhamaneshi et al., 2022) and zero-shot adaptation (Sharma et al., 2020).
Exploratory policies, as another form of prior knowledge, benefit downstream tasks in a different way. Due to the importance of exploration, exploratory policies can provide good initialization for the agent to gather diverse experiences and reach high-rewarding states. For example, Campos et al. (2021) validate the effectiveness of transferring exploratory policies trained by curiosity-driven approaches, in particular for domains that require structured exploration.

While it is always feasible to finetune pretrained policies, considerations should be taken in order to prevent *catastrophic forgetting* when learning in the downstream task. Catastrophic forgetting refers to the tendency of neural networks to disregard their previously obtained knowledge when new information is acquired. To mitigate this issue, one might apply knowledge distillation-like regularization together with RL objectives (Schmitt et al., 2018):

$$ \mathcal{L}_{\text{KD}} = H(\hat{\pi}(a | s) \| \pi_\theta(a | s)),$$

where $H$ is cross entropy and $\hat{\pi}$ is the teacher policy. We refer the reader to Khetarpal et al. (2020) for more discussions on catastrophic forgetting in reinforcement learning.

### 6.3 Challenges & Future Directions

**Parameter Efficiency.** Despite that existing pretrained models for RL have much fewer parameters as compared with those in the field of supervised learning, the issue of parameter efficiency is still important with the ever-increasing number of model parameters. More concretely, it is desired to design *parameter-efficient transfer learning* that updates only a small fraction of parameters while keeping most of the pretrained parameters intact. It has been actively studied in natural language processing (He et al., 2022) with solutions like adding small neural modules as adapters (Houlsby et al., 2019) and prepending learnable prefix tokens as soft prompts (Lester et al., 2021). Built on these techniques, several efforts have been made to enable parameter-efficient transfer with prompting (Xu et al., 2022; Reed et al., 2022), which we believe has a large room to improve with tailored methods.

**Domain adaptation.** In this section, we mainly consider task adaptation where unseen tasks are given in the same environment. A more challenging but practical scenario is domain adaptation. In domain adaptation, there exist environmental shifts between the upstream and downstream tasks. Despite that these environmental shifts are commonly seen in real-world applications, it remains a challenging problem to transfer across different domains (Eysenbach et al., 2021; Huang et al., 2022a). However, we believe that this direction will rapidly evolve by bringing related techniques from supervised learning to reinforcement learning.

**Continually-developed models.** For practical applications, we can take a step forward and consider building large pretrained models continually to support added features (e.g., a modified action space, more powerful architectures, etc). While such consideration was already underway during the development of large-scale RL models (Berner et al., 2019), it requires a more principled way of combining updates into RL models. We refer the reader to recent work in this direction in the field of supervised learning (Raffel, 2021) and reinforcement learning (Campos et al., 2021; Agarwal et al., 2022).
7. Conclusions and Future Perspectives

In this section, we conclude this survey and highlight several future directions which we believe will be important topics for future work.

This paper introduces pretraining in deep RL by discussing recent trends to obtain general prior knowledge for decision-making. In contrast to its supervised learning counterpart, pretraining faces a variety of challenges unique to RL. In this survey, we present several promising research directions to tackle these challenges and we believe this field will evolve rapidly in the coming years.

There are still several open questions that are important and remain to be addressed.

**Benchmarks and evaluation metrics.** Evaluation serves as a means for comparing various methods and driving further improvements. In the field of natural language processing, GLUE (Wang et al., 2019) is a widely used benchmark to evaluate the performance of models across various natural language understanding tasks. Recently, there has been a surge of research on improving evaluation for RL in terms of evaluation metrics (Agarwal et al., 2021) and benchmark datasets (Cobbe et al., 2020). To the best of our knowledge, URLB (Laskin et al., 2020) is the only benchmark for pretraining in deep RL. It presents a unified evaluation protocol for online pretraining based on the DeepMind control suite (Tassa et al., 2018). However, a principled evaluation framework for offline pretraining and generalist pretraining is still missing. We expect existing offline RL benchmarks like D4RL (Fu et al., 2020) and RL Unplugged (Gulcehre et al., 2020) can serve as the basis for developing pretraining benchmarks, but more challenging tasks should better illustrate the value of pretraining.

**Architecture.** As discussed in previous sections, there has been a surge of leveraging large transformers for RL tasks. We expect other recent advances in model architecture can bring more improvements. For example, Mustafa et al. (2022) learn large sparse models with a mixture of experts that simultaneously handle images and text with modality-agnostic routing. This has the promise to solve complex tasks at scale. Besides, one can also rethink existing architectures that have the potential to support large-scale pretraining (e.g., Progress Neural Networks (Rusu et al., 2016)).

**Multi-agent RL.** Multi-agent RL (Zhang et al., 2019) is an important sub-field of RL. Extending existing pretraining techniques to the multi-agent scenario is non-trivial. Multi-agent RL typically requires socially desirable behaviors (Ndousse et al., 2021) and representations (Li et al., 2021). To the best of our knowledge, Meng et al. (2021) present the only effort in pretraining multi-agent RL with supervision. How to enable unsupervised pretraining for multi-agent RL remains unclear, which we believe is a promising research direction.

**Theoretical results.** For RL, the significant gap between theory and practice has been a longstanding problem, and bringing large-scale pretraining to RL may exacerbate this even further. Fortunately, recent theoretical studies have made efforts in terms of representation transfer (Agarwal et al., 2022) and skill-conditioned policy transfer (Eysenbach et al., 2022). Increasing focus on theoretical results is likely to have profound effects on the development of more advanced pretraining methods.
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