Intelligent Robot Manipulation Requires Self-Directed Learning

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Abstract

The Embodied AI community has long aspired to create robotic systems with human-level intelligence and dexterity. Recent advances in vision and language models motivated researchers to follow a similar paradigm for robotics and scale up imitation learning from demonstrations. However, imitation learning lacks the mechanism to incorporate feedback from the agent's own experience during interaction with the environment. This perspective argues that enabling agents to learn from their own experience, which we term as self-directed learning*, is indispensable for advancing the intelligence and dexterity of robotic systems. Despite possessing a similar concept and toolkit to existing reinforcement learning methods, self-directed learning imposes extra challenges that could completely alter the algorithmic landscape of robot learning: the lack of resets and an explicit and noise-free reward signal. To overcome this limitation, we argue that future endeavors in self-directed learning should be focused into three aspects: goal identification, skill acquisition, and performance evaluation. To improve the efficiency of each step, we are inspired by education theory, suggesting that learning is not confined to a single modality, but rather relies on shared mechanisms across visual, textual, and kinesthetic processes. The key challenges and prospective research avenues to self-directed learning are outlined. We further foster a discussion on alternatives to self-directed learning to train robots for physically dexterous tasks.*

1. Introduction

Embodied AI (EAI) aims to build intelligent robotic systems capable of perceiving their surroundings, interacting with the environment, and executing actions based on sensor inputs [77, 93]. Robotic manipulation presents a central challenge in attaining human-level intelligence in robots [55]. This complexity arises from the diversity and intricate nature of manipulation tasks and the objects being interacted with, along with the direct impact manipulation exerts on the robot's environment [23, 55].

In recent years, the emergence of foundation models, such as large language models (LLMs) [74] and vision language models (VLMs) [97], has catalyzed a surge in large-scale machine learning research. By scaling up data and model capacities for behavior cloning (BC), the robotics community has made significant strides in developing large-scale robot datasets to chase the goal of training a general robot policy [16, 51, 76, 100]. These efforts have yielded remarkable outcomes, such as manipulation policies exhibiting improved robustness to variations in object positions, lighting conditions, and background [10, 25, 35]. However, these advancements primarily rely on expert demonstrations and pre-trained large models, which, as recent studies suggest, may limit their adaptability to long-horizon or entirely new tasks [11, 72]. While we recognize the importance of scaling up data for supervised learning as part of the roadmap towards generalization, we argue that the mere scaling of behavior cloning will *not* be sufficient for robots to achieve general dexterous intelligence.

But if this hypothesis is true, what can we do? For insight, we take inspiration from the broader history of human intelligence [95, 102], particularly the Dartmouth workshop [69] where the term "artificial intelligence" was first coined. Artificial intelligence aims to empower machines to master all skills that humans have [8, 23]. Ideally, for a robotic manipulation system to demonstrate intelligence, it must exhibit adaptability across diverse scenarios and be able to evolve and handle new tasks without requiring prior labeled data. We refer to this capability as *self-directed learning*. In essence, this entails the agent's capability for adaptation to generalized goals through self-derived reasoning and guidance. While conceptually related to reinforcement learning, self-directed learning differs in two key ways: it lacks a controlled environment with resets and does not rely on noise-free, carefully engineered reward functions.

In this position paper, we advocate for the development of self-directed learning approaches to surmount the limitations of scaling BC and to fulfill the desiderata for an intelligent robotic system. Drawing on pedagogical theo-

ries [38, 53], we posit that self-directed learning in embodied agents should operate as a closed-loop feedback process, grounded in three core pillars: goal identification, skill acquisition, and performance monitoring or evaluation.

These components should also be developed through learning from unlabeled data and structured exploration, enabling adaptation to new tasks in a self-reflective and continually evolving manner. To bridge the gap between the principles of self-directed learning and real-world deployment, we propose leveraging three human learning strategies (VTK): visual, textual (including auditory and reading/writing), and kinesthetic.

In summary, **this perspective advocates for self-directed learning being the essential component for enabling an intelligent robotic manipulation system**. Although this work focuses on robot manipulation as a testbed for the self-directed learning, these principles might be universally applicable to diverse EAI domains, e.g., robot navigation.

The remainder of this paper is organized as follows. In Sec. 2, we first provide an overview of the task formulation and highlight the primary challenges in general-purpose manipulation (Sec. 2.1). We then propose key principles, processes, and necessities of self-directed learning to address the challenges towards intelligent manipulation systems (Sec. 2.2). We reveal how visual, textual, and kinesthetic learning can be applied for various self-directed learning stages in Sec. 3, while also discussing challenges and potential directions in developing an effective self-directed learning framework in Sec. 4. Finally, alternative views, including scaling up BC, are outlined in Sec. 5.

2. The Principles of Self-Directed Learning

2.1. Formulation and Challenges Involved in Robot Manipulation Tasks

The problem can be formulated as a Goal-conditioned Markov Decision Process (GcMDP), which involves continuous and dynamic interactions with an environment while accommodating diverse objectives [3, 107]. Concretely, it can be represented by the tuple $\langle \mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{G}, r, \gamma, \phi, p_g \rangle$, where $\mathcal{S}$, $\mathcal{A}$, and $\mathcal{G}$ define the state space, action space, and goal space, respectively. $\mathcal{T}$ is the dynamics transition function and γ denotes a scalar discount factor. $\phi : \mathcal{S} \to \mathcal{G}$ denotes a function mapping a state s to a specific goal $g \in \mathcal{G}$, and p_g represents the distribution of desired goals. The state and goal space typically involve objects for manipulation, environmental background, and some relational or behavioral descriptions about the current and desired status. Variations in $\mathcal{S}$ or $\mathcal{G}$ are often referred to as generalization problems [11, 35]. While the latter is general, we argue for an alternative task formulation that is more practical and clearly highlights pronounced deviations from the training data distribution.

A manipulation task begins at time step $t = 0$, and concludes at $t = T$ upon meeting a termination condition, which could involve reaching a time limit or receiving success or failure signals. The sequence of state-action pairs, $\{s_t, a_t\}_{t=0}^{T}$, is referred to as an episode. Typically, the robot receives a sparse reward indicating success, set by $r : \mathcal{S} \times \mathcal{A} \times \mathcal{G} \to \mathbb{R}$. The objective is optimizing the goal-conditioned policy $\pi : \mathcal{S} \times \mathcal{G} \to \mathcal{A}$. Next, we delineate the challenging settings for real-world manipulation, and introduce corresponding requisite elements to achieve dexterity in Sec. 2.2.

Long-Horizon Tasks. Current prevailing benchmarks focus on simplified laboratory settings with single or limited motions involved [70, 109]. Meanwhile, there are substantially more complex long-horizon manipulation tasks which test a robot in the real world. For instance, a simple household task such as "`bring me a snack from the drawer`" involves at least four sub-goals: opening the drawer, picking up the snack, delivering it to the user, and closing the drawer at the end. Complex tasks like "`wash the dishes in the sink`" will yield more sub-processes to achieve the final target. Since the entire process is temporally dependent, even minor deviations in achieving any of these sub-goals can lead to overall task failure.

In particular, a *desired goal* is defined as the ultimate objective, with a binary reward $r \in \{0, 1\}$ awarded at episode completion. In addition, *behavior goals* are introduced to represent intermediate objectives throughout the episode. Real-world task goals can manifest in various forms, including textual instructions [1, 52], target images [50, 108], or specified locations and motion references [19].

Lack of Privileged Information. Though not explicitly formulated as a partially observable MDP with state estimations in many robot manipulation works, full and accurate observation and transition dynamics are often not available. Unlike tasks with full privileged information [96], robots rely on limited sensory inputs, such as RGB-D images captured in first-person, third-person, or wrist views, and tactile sensors mounted on grippers and dexterous hands. However, even with multi-modal inputs, comprehensive environmental information remains elusive due to viewpoint constraints, occlusions, and unattainable object-specific knowledge like the gravity center and friction parameters [71, 104]. Most importantly, rewards for long-horizon tasks are very challenging to engineer.

In robot manipulation benchmarks, evaluation is typically conducted by humans or simulators with privileged knowledge of the environment's states [70, 76, 109], such as objects' contact status. The evaluator assigns a reward of $r = 1$ if the task is completed at the end of the episode and sometimes partial scores for the completion of sub-

goals, *e.g.*, $r = 0.5$ for achieving the first sub-goal in a two-sub-goals manipulation task [36]. However, the aforementioned partially observable nature of robotic perception severely undermines this requirement for sub-goals' verification, leading to failures in long-term tasks' generalization.

2.2. Principles of Self-Directed Learning

Conventional robotic systems deployed in physical environments are typically human-directed in terms of goal setting, data collection, and progress monitoring. For instance, perception and planning algorithms are divided and integrated into an engineered system, *e.g.*, a combination of detectors, a state machine, and A* planning. Handcrafted rules are devised to cover most situations robots may encounter, with meticulously selected data employed to train independent modules. Although adequate for constrained applications such as industrial robots, this paradigm exhibits limitations in generalizing across different environments and embodiments [23].

Recent advancements in LLMs offer an alternative path towards generalization requiring reduced human intervention. Leveraging extensive textual data sourced from the internet, LLMs adopt a unified model encapsulating a vast array of world knowledge, demonstrating an impressive ability to interpolate and extrapolate for adaptation [74, 97]. Unfortunately, most contemporary robotic systems fail to exhibit a comparable level of generalization, especially in novel or long-horizon tasks requiring self-reflection and self-adaptation. In contrast to the unified text data, robot data is usually collected through teleoperation or simulations, with task specifications manually defined including goals and optimization targets. While popular end-to-end methodologies benefit from scaling techniques and building upon LLMs/VLMs to establish strong perception and memory foundations, they still struggle with complex physical interactions [17, 27, 76]. For example, systems like OpenVLA [52] often work only within the confines of the same environment and embodiment used during training, which indicates only interpolation capabilities rather than extrapolation and adaptation (we refer to Sec. 5.1 for detailed discussions on scaling behavior cloning).

EAI systems are generally composed of four key components: perception, action, memory, and learning [77]. While recent end-to-end approaches have made significant progress in scaling unified models that implicitly integrate perception, action, and memory [6, 20, 27, 52, 98], the learning component remains underdeveloped. Here, we define learning broadly as the ability to generalize—to make accurate predictions under novel input distributions [37, 95]. At the same time, there is growing recognition that open-endedness, i.e., the capacity for continual, unsupervised skill acquisition, is essential for the emergence of intelligence [44]. To foster such adaptive capabilities, especially once existing robotic datasets have been exhausted, advancing the learning module in robot systems is critical.

In this vein, **self-directed learning** from data and experience in the wild, instead of relying solely on pre-scripted paired demonstrations, emerges as a viable direction. To be specific, given the current state s, the desired goal g, and a base goal-conditioned policy π, where s and g significantly deviate from prior experience and render π inadequate for achieving g, the robot needs to autonomously adapt and evolve to the new task without pre-collected perception-action demonstrations. This learning paradigm mirrors the self-directed learning in human education [38, 53]. It can be divided into three main steps: **(1) set learning goals, (2) engage in learning to acquire skills, and (3) monitor and evaluate learning progress and outcomes**. One essential feature of this paradigm is the closed-loop structure which facilitates adaptive progress towards the ultimate goal [95]. Consequently, to address the challenges posed by long-horizon goals and the absence of privileged information in general-purpose manipulation, advancements in all three dimensions are desired.

2.2.1. Step 1: Goal Identification

Task Decomposition. As mentioned in Sec. 2.1, a complex long-horizon task usually involves multiple stages, with a specified desired goal. While behavioral goals can be generated either by the environment or human monitors given the desired goal, we emphasize the intrinsic goal setting due to the lack of privileged information and human labelers. Specifically, the robot must *autonomously generate sub-goals* for learning based on the desired goal provided in the instructions without external intervention. A primary advantage is that the identified sub-goals naturally guide the policy to achieve the ultimate target during both the learning phase and deployment.

State Space Abstraction. Though most existing robot manipulation benchmarks employ high-level language instructions to represent desired goals [16, 51, 76], they can be abstracted and provided in multiple forms. Text-based representations are widely favored due to their human-friendliness and universal format, akin to their utility for foundation models [74]. Besides, depicting goals in an image format is also feasible [2, 29, 30]. In limited manipulation tasks like object reorientation [67, 81], the target is a numeric position with which dense rewards can be calculated precisely. These various forms do not have substantial advantages over each other, and would be applicable in different learning strategies, as elaborated in Sec. 3.

For robotic manipulation in the real world, goals often highlight the most relevant content about task rewards. Thus, the goal space is typically a sub-space of the full state space (*i.e.*, $\mathcal{G} \subset \mathcal{S}$), and goal identification functions as a state abstraction [41, 79]. Besides, given that goals are

the conditions for skill acquisition and reward evaluation in GcMDP, the clarity and propriety of identified goals are crucial to guide the learning process, affecting the efficiency and efficacy of self-directed learning.

2.2.2. Step 2: Skill Acquisition

We consider a setting in which no paired data between perception and robot actions is available. Even if the goals and evaluation mechanisms are predefined, the lack of labeled data demands that the robot acquire new knowledge autonomously.

Skill Transfer. Humans possess the ability to acquire new skills through demonstrations, such as mastering a dance routine, even in the absence of precise action annotations. Robots should reach similar competence by adapting to new skills by utilizing non-identical exemplar data formats. This skill transfer process is analogous to the concept of in-context learning, a trending and encouraging direction in foundation models, where pre-trained LLMs can be boosted based on augmented examples [13]. However, our target skill source diverges from the text expressions for LLMs. In the realm of robot manipulation, demonstrations can stem from heterogeneous data sources, including human videos, similar rollouts of robots with distinct embodiment configurations, or even instruction books [17, 47, 89]. Though limited paired data is present at this stage, a vast amount of mixed data in the wild can be leveraged for this purpose.

Skill Acquisition from Scratch. When no valuable internal memory or external resources can be retrieved, the system has to search on its own. Yet, prior research in reinforcement learning (RL) areas has demonstrated that exploration in the vast state and action space is extremely inefficient [46, 61, 109], which raises further demands for an effective monitor to guide the learning direction.

2.2.3. Step 3: Monitoring and Evaluation

Self-directed learning is a closed-loop and dynamic process, where evaluation of the learning progress provides feedback to the agent to adjust the subsequent learning direction [53]. This can sometimes be referred to as *self-reflection* [63]. For robots, the core of self-reflection lies in their ability to evaluate their behavior process and causally determine their actions [2]. As discussed in Section 2.1, long-horizon tasks in robotics are typically decomposed into several stages, referred to as behavioral goals, and it is essential to enable the system to detect errors and ensure that each intermediate goal is reliably achieved before proceeding to the next sub-goal. We usually evaluate the task progress or success status with signals from the simulators or supervision from humans aside the robots. However, in a fully autonomous, self-directed setting, we need to define an explicit distance function $d(\phi(s), g)$ to measure the distance between the state and the goal in $\mathcal{G}$ and set a threshold ϵ to assess whether the agent has achieved its goals, without access to privileged information as in simulators.

Specifically, we express the distance function as a **value model** V, which quantifies the "goodness" of a given state s_t. While a state-action value function $Q^\pi(s_t, a_t)$ (or Q-function) is conditioned on the action a_t, our focus in this work is on learning the *state value* alone. Importantly, although value functions are often associated with RL, our framework does *not* require the use of RL algorithms. The value estimate can be learned jointly with the policy or obtained independently. For example, it may be instantiated as a classical value function trained via RL [73], or as a VLM that predicts task progress as a proxy for value [7, 45].

Thus, while we adopt the formalism of MDPs and emphasize the utility of value learning, our method deliberately decouples value estimation from reward-based interaction or trial-and-error learning. The value function serves as a flexible signal that can support both policy training and test-time monitoring. To this end, value learning helps to use the value function as a metric to detect the intermediate failure modes and task progress during deployment. We refer to this as *closed-loop feedback* or error measurement in this work. This capability can be applied to two major perspectives: (1) verifying the reliability of self-generated behavioral goals, (2) determining the appropriate time to transition to the next sub-goal by assessing the progress or completion of the task.

Sub-Goal Verification. Since the sub-goal sequence is directed toward the ultimate target, which receives a reward of $r = 1$, the intermediate values should, in principle, increase monotonically from 0 to 1 after reward shaping. With a reliable value estimate, it becomes straightforward to check if the value falls below a specified threshold or decreases significantly compared to previous sub-goals. A small threshold ensures that sub-goals are completed and that the transition to the next sub-goal or task termination occurs successfully. When these conditions are met, the agent can re-plan and generate a new set of behavioral goals to correct the course of action and manage long-term tasks.

Outcome Assessment with Closed-loop Feedback. Taking both the value and the goal, the distance between these two states can be expressed as $d(\phi(s), g) = V^\pi(s) - V^\pi(\phi^{-1}(g_k))$. Distinct from approaches involving fixed sub-goal action prediction and execution, this allows the agent to progressively advance toward the goal. This approach is consistent with the closed-loop feedback philosophy, where the error serves as guidance for the next sub-goal and benefits causal reasoning [15, 68].

3. Potential Strategies for Self-Directed Learning

Motivated by the principles outlined in Sec. 2.2, we demonstrate potential learning strategies to fulfill the proposed

self-directed learning paradigm in this section. Fundamentally, any candidate that tackles all the three steps above would be an effective implementation. However, we focus on a set of strategies inspired from education theory. Specifically, we categorize such strategies into three classes (VTK): visual, textual (including auditory, reading/writing), and kinesthetic. The categorization follows a soft standard from pedagogy theories, as will be presented in Sec. 3.1. Then, we discuss in detail what each class of works has achieved, and what aspects they are still missing for enabling general robot manipulation.

3.1. Background of VTK Learning Strategies

Since the 1970s, educators have investigated how individuals differ in learning, which has led to the development of modern education theory. One widely acknowledged model is categorized by learning modalities. In particular, Barbe et al. [5] proposed that there are mainly three types of learners: visual learners, auditory learners, and kinesthetic learners (VAK learning styles); and one style is often predominant for each individual's learning preference. Fleming et al. [34] further extended the theory with one additional modality, *i.e.*, reading/writing, leading to the VARK model.

For robotic systems, visual and kinesthetic skills can be reflected in the perception and action modules [77]. However, auditory and reading/writing abilities are not exactly developed like humans; but often exist in another form of the input and output of the system–text. For example, auditory instructions are usually transformed into text with a speech recognition model, and then processed by foundation models [74, 82]. Thus, in this paper, we merge these two learning strategies as a whole to be textual learning for better analyzing current advancements in robot manipulation. The resulting visual, textual, and kinesthetic learning strategies are then abbreviated as VTK learning. We compare below how VTK learning strategies differ from each other, along with their connection to the original VARK learning styles in human education:

- Visual learning: The agent imitates humans' or other experts' demonstrations via visual information (images, videos, or data from other visual sensors). This is similar to human visual learners who absorb information primarily by observation.
- Textual learning: Learners follow text-based demonstrations or involve text-based abstraction to accomplish a task (*e.g.*, aided by foundation models).
- Kinesthetic learning: The learning happens mostly through online physical interaction with the real world (usually implemented by reinforcement learning with more modalities such as tactility). This is analogous to kinesthetic learners who actively participate in hands-on activities or events.

3.2. Visual Learning

Most elemental human activities originate from the imitation of others' behaviors through the visual system. As incorporating visual imitation in robot learning is promising, many works focus on visual learning in robotics, aiming to extract valuable semantics from visual observations, potentially form a series of sub-goals to accomplish a task, and finally predict executions to reach the sub-goals/goal.

Numerous works design perceptual tasks to extracting semantic clues from visual demonstrations. Such cues are then used to compute robot actions. These demonstrations may involve hand trajectories [18, 87, 92] or poses [90, 101], as well as semantic contact points [94] and affordances [4, 56, 87]. The extraction process leverages advanced vision models [78, 84] in an off-the-shelf fashion [56]. The extracted semantics are then utilized either as action labels for imitation learning within the policy network [32, 113], or as perception labels for fine-tuning the perception model followed by execution by a low-level controller [11, 33].

The construction of sub-goals has been an active topic in visual learning, aiming to predict possible future frames based on the current frame and the corresponding semantics. This predictive model is sometimes presented as a world model in the literature [29, 42, 54]. This is done by synthesizing a video of the imagined execution of the task using a video prediction model [40] conditioned on the initial frame. The predicted frames are either directly employed by the visuomotor policy [15, 54] or utilized for extracting sub-goal semantics, subsequently translated into sequential actions [29].

3.3. Textual Learning

Advanced human activities, such as assembling IKEA furniture following a user manual, demand the capacity to comprehend text-based instructions and execute them step-by-step to accomplish the task. With the advent of LLMs/VLMs, it is attractive to utilize them either directly or through fine-tuning to mimic the procedure of learning from text-based demonstrations. This approach typically involves converting the task completion process to text, constructing text-based demonstrations [79, 111], and employing LLMs/VLMs to finish the task via in-context learning or supervised finetuning.

The first stage is to generate the textual description of accomplishing a task (demonstrations) with the help of LLMs/VLMs [74, 97]. This involves image understanding and reasoning about the task completion [111, 112], both of which may or may not include the final executable action. The second stage is to utilize the in-context ability of the off-the-shelf LLMs/VLMs to infer on the new tasks with the generated demonstrations as a prompt, followed up with vision-language-action models (VLAs) [14, 52, 113]

or other task executors to finish the task.

What is Missing in Visual Learning and Textual Learning? These works moderately address the Step 1 in the proposed self-directed learning (visual learning has predicted future frames [54] and textual learning has the text-based decomposition for accomplishing a task [111]). However, many of them neglect the monitoring and evaluation of their predicted actions when trying to reach sub-goals (Step 3) and thus may "blindly" execute the predicted sub-goals during inference. Recent works are dedicated to providing the proposed monitoring and evaluation by evaluating the intermediate sub-goals of the task completion via VLMs [66] or a video prediction model [31, 43], which is feasible but also introduces more challenges as discussed in Sec. 4.

3.4. Kinesthetic Learning

Indirect learning strategies such as visual and textual learning entail robots retrieving demonstrations from external sources for skill transfer. In contrast, kinesthetic learning represents a more direct approach, emphasizing learning through hands-on interaction with the physical environment, *e.g.*, manipulating the robot around physically to find the task's solution. Kinesthetic learning, particularly in the realm of reinforcement learning within simulated environments and subsequent policy transfer to real-world settings, encounters challenges in large-scale deployment due to issues inherent in simulation construction and the sim-to-real disparity [23, 37, 106]. An emerging trend in addressing these challenges lies in real-world RL [58, 64, 65], where actions from the policy network are applied to the physical robot directly. This line of research, while promising, has not been as extensively explored as visual or textual learning strategies, regarding core issues such as safety protocols for human-robot-interaction, data sampling efficiency, and the variance in real-world feedback.

What is Missing in Kinesthetic Learning? RL frameworks can provide the utility of monitoring and evaluation (Step 3) of the predicted actions via rewards or similar mechanisms, yet many of them tend to overlook or underemphasize the crucial step of goal identification (Step 1). Alternatively, hierarchical RL frameworks, closely related to goal identification, have only been demonstrated in constrained environments and short-term tasks [57, 103]. These limitations diminish the transferability of acquired skills, as no intermediate atomic actions are shared explicitly across diverse tasks. Furthermore, even RL-based methods fall short in adequately addressing monitoring and evaluation aspects, with challenges persisting in learning a general reward function itself [46].

4. Challenges and Future Work

Ambiguity in Value Annotation and Estimation. The value function models the latent distance between goals and states. Therefore, analogous to the aforementioned goal abstraction issue, generating annotated data for supervised learning or reinforcement learning of value functions for complex tasks is non-trivial. For example, having a human labeler assign scalar value functions for robot data at scale is challenging, due to the inherent ambiguity in the definition (*i.e.*, sub-goals) of this task. One potential alleviation to obtain data with value estimates often requires a separate stage of online RL or rule-based planning with known reward functions [85]. Annotating preferences or comparisons between states, as is common in reinforcement learning with human feedback for LLMs, is another interesting avenue to explore for this task [83].

Meanwhile, due to the ambiguity of goals, precise value estimation is challenging as well. Despite the extensive applications, existing value learning approaches for real-world robots are typically formulated as sparse success detectors based on image observations [28, 30, 108]. In many cases, these value functions can be insufficient, as they do not fully capture the three-dimensional and physical states and cannot indicate the task progress, making it challenging to evaluate nuanced state transitions in dexterous tasks. How to enable more precise value estimation and incorporate more informative factors such as multi-modal sensory data for value estimation remain underexplored.

Generalized Value Learning. The multi-goal setting demands the value function to be robust in diverse or even novel scenarios, necessitating a universal value function approximation [86]. This could raise similar challenges as learning the policy itself. Nonetheless, current value learning approaches are often established on simple or simulated tasks [15, 66, 67]. As a result, they may suffer from covariate shifts when applied to the real world. This discrepancy can lead to suboptimal executions, as the accuracy of the learned value functions may drop severely across varying conditions. This highlights the need for diverse data for value learning. Potential solutions may include leveraging the generalization of foundation models [7, 28, 68] and domain adaptation techniques.

Integrated VTK Learning. While different learning strategies (visual, textual and kinesthetic) have demonstrated promising results in certain perspectives of self-directed learning, how to effectively integrate them together to cover the full learning stages and enjoy the best of them remains puzzling. As visual and textual learning are mainly implemented as imitation learning, and kinesthetic learning usually employs reinforcement learning, a natural idea is to combine them in the training procedure. For instance, one potential direction is to learn a residual policy via RL using controlled exploration strategies [48]. The residual compo-

nent learned with kinesthetic strategies may serve as an additional value estimator, and be integrated with the base policy cultivated with visual and textual learning. Yuan et al. [110] propose Policy Decorator as it functions similarly to Python decorators—wrapping with additional error correction the base policy learned from visual or textual learning. Such error correction ability initially comes from the goal identification and progress monitoring capability of the base policy while evolving during RL training, making the ultimate solution cover all three steps in the self-directed learning process.

5. Alternative Views

In this section, we outline two alternative paradigms to self-directed learning: "full" human involvement in deciding the goals, values, and learning by scaling up behavior cloning (Sec. 5.1), and "partial" human involvements, where humans focus on error correction and feedback (Sec. 5.2).

5.1. Scaling Behavior Cloning

Built upon the rapid advancements in both AI software and hardware infrastructure [91, 99], scaling laws have been demonstrated in domains such as LLMs/VLMs [74, 97] and vision generators [12, 80]. They exhibit generalization abilities such as instruction following [75] and few-shot learning [13]. The robotics community, pursuing the same goal of generalization, could potentially reproduce similar successes. The primary motivation for adopting scaling BC in robotics is that it circumvents a case-by-case sophisticated design for each task, or structured VTK learning paradigms to incorporate unannotated sources, and embraces the generalization learned from data at scale. Researchers have made substantial efforts in this direction, including collecting large-scale demonstrations [16, 51, 76, 100] and leveraging pre-trained foundation models to build VLA models [9, 52, 59, 62]. One might argue that extremely comprehensive data coverage could resolve issues such as goal identification and value modeling in new tasks [25], especially with the help of simulation and low-cost devices for crowdsourcing, while also revealing some limitations worthy of further exploration.

Memorization instead of Intelligence. Although recent works [25, 52, 59, 62] demonstrate that increasing the size of both the pretraining dataset and the model improves success rates and the ability of instruction following, they still fail to generalize across unseen tasks and environments. One possible explanation is that large-scale imitation learning in robotic data is merely memorizing the data distribution from the collected demonstrations [22, 39]. The lack of failure data in training also constrains models, resulting in an inability to self-correct and self-improve.

A Plateau with Scaling Behavior Cloning. Even when success rate is considered the primary metric, the typical 'scaling law' appears to be invalid for robotic models, as it reaches a plateau rather than following the expected power-law relationship [49] with respect to data and model size [72]. This plateau in performance has been observed in several models pretrained on the Open X-Embodiment dataset [76], including RDT-1B [62] and Octo [98]. Even when expanding generalization across multiple embodiments [26], a power-law relationship does not emerge as expected.

5.2. Human-in-the-loop Learning (Assistive Training)

Note that an important property of self-directed learning is that it is highly self-motivated and monitored, *without* external intervention, or with minimal interference. However, as in traditional classroom education, teachers are still occasionally necessary to provide feedback to the self-directed learners [53]. Human-in-the-loop learning (HITL) has demonstrated success in LLM post-training, utilizing RL to align with human preference [75] or select valuable training data to strengthen certain abilities [24]. Similarly, in robot learning, HITL also presents great promise for these benefits. This could make learning more efficient as humans inherently introduce privileged information that is previously inaccessible to robots.

With a base policy, monitors can take over or send real-time instructions to manipulation systems to correct mistakes and guide exploration directions [21, 60, 65, 105]. The error correction data involved may be helpful to enhance the causal reasoning ability of the robot. The resulting action sequences can be leveraged to continuously update the policy with RL [65] or BC [60]. Witnessing these advancements, an alternative opinion against self-directed learning might stand that we can employ HITL for adapting to complex tasks and learning value functions with the monitors' feedback efficiently. However, one crucial issue has inevitably obstructed its broader application.

Limited Scalability. In scaling behavior cloning (Sec. 5.1), researchers have addressed scalability challenges by leveraging low-cost hardware and large-scale simulation data. In contrast, human-in-the-loop (HITL) algorithms present several fundamental obstacles to scalability. First, they require real-time human intervention during robot execution, without halting rollouts. Most existing work relies on collaborative robots to support this need [60, 65], as few other hardware platforms offer the reliability and integration ease needed. Second, effective human feedback requires accurate and responsive teleoperation systems to correct robot behavior, which is especially demanding for tasks involving end-effectors or dexterous hands [21, 105]. Third, recent approaches have explored incorporating high-level human feedback during task execution [88]. However, this assumes the presence of a strong low-level policy that

can meaningfully interpret human intent—an assumption that often limits applicability to narrow, well-defined tasks rather than general settings. Across all these approaches, the need for skilled teleoperators or monitors introduces serious barriers to both scalability and safety, posing a major challenge to the widespread adoption of HITL methods for advancing robotic manipulation.

6. Conclusion and Outlook

In this work, we argue that an intelligent robot manipulation system should prioritize developing self-directed learning abilities, including autonomous goal identification, policy learning, and monitoring with a value model. Although scaling techniques have achieved significant success in numerous domains, we argue that scaling alone is insufficient to realize the goal. Instead, we propose that robots can achieve self-directed learning inspired by human learning styles, through visual, textual (auditory, reading/writing), and kinesthetic learning.

As the field of Embodied AI continues to evolve rapidly, it is clear that algorithmic breakthroughs do not occur in isolation. As discussed above, progress in areas such as hardware design, data collection, and ecosystem will also be essential to unlock the full potential of self-directed learning. We anticipate that advances in self-directed learning for robots will not only drive innovation across robot manipulation, but may also inspire progress in adjacent domains beyond robotics.

Impact Statement

The method described in the paper aims to advance the intelligence of robot manipulation. To equip the model with correct value estimation ability, training data may involve both successful demonstrations and failure recordings in the form of broad human activities and robot rollouts, which potentially contain unsafe materials and require sophisticated AI safety supervision. Besides, the real-world deployment of current robot manipulation systems needs responsible human oversight to ensure safety.

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