Grounding Hindsight Instructions in Multi-Goal Reinforcement Learning for Robotics

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Abstract—This paper focuses on robotic reinforcement learning with sparse rewards for natural language goal representations. An open problem is the sample-inefficiency that stems from the compositionality of natural language, and from the grounding of language in sensory data and actions. We address these issues with three contributions. We first present a mechanism for hindsight instruction replay utilizing expert feedback. Second, we propose a seq2seq model to generate linguistic hindsight instructions. Finally, we present a novel class of language-focused learning tasks. We show that hindsight instructions improve the learning performance, as expected. In addition, we also provide an unexpected result: We show that the learning performance of our agent can be improved by one third if, in a sense, the agent learns to talk to itself in a self-supervised manner. We achieve this by learning to generate linguistic instructions that would have been appropriate as a natural language goal for an originally unintended behavior. Our results indicate that the performance gain increases with the task-complexity.

Index Terms—reinforcement learning, language grounding, instruction following, hindsight instruction, human-robot interaction

I. INTRODUCTION

Enabling robots to ground language in action has been ongoing research for decades [1]–[4]. Language is often the most important communication channel for human-human and human-robot interaction (HRI). More recently, researchers made progress in robotics, utilizing language to learn diverse behaviors and understand instructions within simulations [3] and the real world [5]. However, these learning approaches are still not on par with the zero-shot learning capabilities of human infants. Machine learning methods require huge amounts of offline data, large pre-trained models and many human-based language annotations. In this article, we ask how we can improve the sample-efficiency and alleviate the need for language annotated robotic datasets.

In our recent review on embodied language learning [6], cognitive principles emphasize the importance of linguistic feedback that toddlers experience while they explore in an intrinsically motivated fashion or imitate their social partners and caretakers. Here, we want to transfer these findings to HRI, where natural language allows describing goals and conditions. An important feature of natural language is its compositionality: it enables the capability to change the context of an utterance in the presence of a wrong outcome. For example, consider the scene in Figure 1, where the robot’s task could be to “touch the green object” (●). Since the object is no further defined, the color-difference determines the correct understanding, and all other properties can be ignored. Similarly, an example with the task to “reach the cuboid” (○) can be considered respectively. This, combined with an external teacher to signal whether instructions have been followed correctly, enables a possibility to ground language about actions, colors and shapes in sensorimotor experience. However, a problem is that the natural language instructions are often misunderstood, leading to erroneous robotic behavior. The problem that we address in this article, is to learn from misunderstood instructions.

Fig. 1: A scene from our simulated LANRO environment with the Franka Emika Panda robot and two objects. An instruction like “reach the green cube” informs about the goal.

A promising solution to address potential failures in robotic learning is hindsight learning [7], [8]. Hindsight methods enable learning from undesired outcomes by treating them as desired ones. Technically, they relabel a present behavior with a goal or instruction that was actually satisfied. A well-known approach is Hindsight Experience Replay (HER) [7] which solved many multi-goal reinforcement learning (RL) tasks with sparse rewards that were entirely unsolvable or where contemporary methods achieved only poor performing solutions. However, HER was initially designed for goals-as-states and is not trivial to adapt for linguistic instructions.
This shortcoming has been addressed by the implementation of HIGHER [9], where the authors exploit the reward signal to collect positive behavior-instruction samples. They use these pairs to train a discriminative model, which predicts instructions that appropriately describe a goal state in a discrete grid world environment.

However, there exists no research beyond the grid world, towards continuous robotic environments with realistic dynamics, where an approach akin to HIGHER [9] is used. This is more challenging because in robotics, the mapping between desired goal states and appropriate instructions to achieve them is \( \infty \)-to-one. For example, consider the complex context-specific continuous-world behavior related to instructions involving grasping and pushing. In this article, we address this gap with the following three contributions:

- **Hindsight Expert Instruction Replay (HEIR)** is a replay mechanism to relabel instructions that led to unintended behavior with hindsight expert instructions that are appropriate for the unintended behavior. For example, consider that an agent has been instructed to “reach the green cube”, but it reaches the blue one. Then HEIR is a method that uses a hard-coded environment-specific language generator to relabel a training episode with a retrospectively correct instruction, which in this case would be “reach the blue cube”.

- **Hindsight Instruction Prediction from State Sequences (HIPSS)** replaces the hard-coded environment-specific language generator with a seq2seq learning mechanism to generate the hindsight expert instructions. HIPSS is self-supervised, in the sense that it automatically generates training data based on the reward signal and grammatical constraints as background knowledge.

- **LANguage RObotics (LANRO)**, a novel class of environments for language-conditioned RL with synthetic instructions and hindsight expert features.

We hypothesize that external hindsight instructions generated by HEIR allow an agent to exploit the compositionality of language by accelerating and stabilizing the training procedure. Inspired by HIGHER [9], we also hypothesize that the training procedure can be accelerated if the hindsight instructions are self-generated with our HIPSS method. To address these hypotheses, we extend the widely used and standardized interface of OpenAI Gym [10] with linguistic goal representations and hindsight instructions (LANRO).

In the remainder of this article, we first highlight the current approaches to language-conditioned and hindsight learning in Section II. With Section III, we provide the theoretical background in goal-conditioned problem-solving. Then, Section IV presents our implementation details, followed by our experimental setup and results in Section V. We close the article with a discussion in Section VI and a short conclusion in Section VII.

II. RELATED WORK

A. Language Grounding in Reinforcement Learning

In the review of Luketina et al. [11], the authors highlight the applicability of language in RL, not only as another type of goal definition but also as a source of information for problem-solving. To this date, most of the studies investigated skill learning with sparse rewards [7], while only some of them incorporate language as part of the observation [4], [12], [13], enabling language grounding based on rewards.

One exceptional example using language to describe goals in RL is the BabyAI platform [14]. It provides integrated expert demonstrations, causal puzzles, human-in-the-loop capabilities, and a synthetic subset of the English language, called BabyLanguage. In environments like the DeepMind Lab [13], the agent is situated in a simple simulated world and instructed to solve navigation tasks using a narrow action space. Furthermore, there exists experiments with language grounding in video games like ViZDoom [15]. However, video games often have a very limited control and sensor space.

Based on our previous surveys [6], [8], we assume that a physically realistic interaction space is crucial for advances in language grounding because it involves continuous actions to explore concepts such as light or heavy and complex motions like grasping or pushing. Such concepts are vital for instruction-following in HRI [2], [3]. However, most existing language-based robotic applications only learn from successful trials [12], [13], while only some of them retry on failure [3] and are capable of logically combining multiple requests [4], [5]. To investigate language-conditioned RL, we consider established methods for goal-conditioned RL [7], [16], [17].

III. BACKGROUND

In this section, we briefly discuss the methodology of RL, especially multi-goal RL and language-conditioned RL. As a central part of this work, we introduce the formal notation of hindsight learning for goals and instructions.

A. Reinforcement Learning

We use the well-known definition of the Markov decision process (MDP), found in the book by Sutton et al. [18]. In this work, the MDP is discrete in time; hence, we annotate the elements with a subscript to specify the current time step. For the multi-goal setting, we augment the MDP by an \( \pi \) that selects actions, \( a \sim \pi(s) \), to maximize the expected cumulative discounted reward \( E_\pi[\sum_{t=0}^{\infty} \gamma^t r_t] \).

B. Multi-goal and language-conditioned RL

For the multi-goal setting, we augment the MDP by an additional set of goals \( \mathcal{G} \) [7], which are part of the state-space, therefore \( \mathcal{G} \subseteq S \). This property allows to map any state \( s \in S \) to a goal \( g \), that we define as mapping function \( m(s) : S \rightarrow \mathcal{G} \). We modify the traditional reward function to compute the reward based on the episodic goal

\[
    r_t = R_g(s_{t+1}, g) = \begin{cases} 
    0, & \text{if } ||m(s_{t+1}) - g||_2 \leq \epsilon \\
    -1, & \text{otherwise} 
\end{cases} \tag{1}
\]
where $\epsilon$ is a task-specific threshold. The reward function $R_g(s_{t+1}, g)$ considers the achieved goal state $s_{t+1}$ and the desired episodic goal $g$ as input. To apply this notion to linguistic goals $g_t$, we remove the mapping function $m(s)$ and replace the if-clause of Equation 1 with a task-specific condition $C(s_{t+1}, g_t)$ that is true if one of the many possible states of $S_g \subset S$ ($g_t$ describes) is achieved with a transition $(s_t, a_t, s_{t+1})$ leading to a state $s_{t+1} \in S_g$:

$$r_t = R_g(s_{t+1}, g_t) = \begin{cases} 
0, & \text{if } C(s_{t+1}, g_t) \\
-1, & \text{otherwise}
\end{cases} \tag{2}$$

In both cases, we assume to sample a state-goal pair $\rho(s_0, g)$ or state-instruction pair $\rho(s_0, g_t)$ respectively at the beginning of each episode, while $\rho$ defines the distribution of start configurations. From the work of Universal Value Function Approximators [16], we know that all the theoretical formulations around the Bellman equation still hold, and we can learn universal policies that can solve linguistic goals if not any type of goal representation [19].

C. Hindsight RL

Hindsight experience replay [7] usually assumes access to the function of Equation 1 to relabel trajectories by transforming visited states into goals a posteriori. Formally, the agent experiences a sequence of transitions $\{(s_0, a_0, r_1, s_1), \ldots, (s_{T-1}, a_{T-1}, r_T, s_T)\}$ up to the episode limit of $T$. For the terminal state $s_T$, a goal $g$, one can evaluate the reward function from Equation 1. In case of a penalty $r_T = -1$, $g$ could be replaced with $g' = m(s_T)$, the corresponding goal that the final state maps to. This cannot be directly used for language-conditioned RL, as it assumes every visited state $s_i$ to be a potential goal. Unlike previous articles [4], [9], [12], we address this issue by using the condition of Equation 2 to detect interactions with any object, therefore linguistically relevant states.

IV. METHODOLOGY

For our agent implementation, we use the Soft Actor Critic (SAC) [17], a state-of-the-art off-policy algorithm commonly used in RL research for continuous perception and control. The implementations HAL [12] and deestr [4] are examples using SAC for instruction-following.

Hindsight learning alleviates the imbalance of successful and unsuccessful trials within the agent’s replay memory, by relabeling the failures with appropriate instructions and sparse rewards in hindsight. This augmentation technique based on contrived transitions not only improves the sample-efficiency, but also the language learning performance [4], [12]. Similar to language development of toddlers [6], we use two methods to obtain the hindsight instructions.

A. Expert Feedback

Prior works [4], [14], [20] have shown, that a social partner [4] or task expert [21] amends the learning of an artificial agent. They can provide linguistic feedback, as they have the knowledge to label the observed behavior with a suitable instruction after the fact. Formally, an expert returns an instruction for a sequence of states $(s_0, s_1, \ldots, s_t) \rightarrow g_t$, the hindsight linguistic goal. In this paper, we use a mechanism derived from HER [7], called HEIR with 3 replay strategies:

- **episode:** Given an episode with a hindsight expert signal at time $t$, we randomly select $k$ transitions within $i$, while $0 \leq i \leq t \forall i$, and relabel them with the hindsight instruction and a sparse reward of 0.0 if $i = t$ or a reduced penalty of $-0.9$ otherwise. This should reinforce the agent to rate those transitions as valuable in satisfying the hindsight goal instruction.

- **future:** For a given episode with a hindsight expert transition at time $t$, we randomly select $k$ transitions from $i$, while $t \leq i < T \forall i$, and relabel them with hindsight instructions and a sparse reward, if $i = t$ or a reduced penalty otherwise. This should incentivize the agent to consider the transitions after the hindsight signal of high quality, as they are similar to the desired goal state or preferable aftereffect of a successful behavior.

- **final:** For an episode and the hindsight signal at time $t$, we consider the last transition at time step $t$ and the immediate $k$ predecessors back to $t - k$ as replay candidates. In both cases, we replace the instruction with our hindsight instruction and substitute the reward with a sparse reward or a lowered penalty, respectively.

B. Discriminative Approach

The agent uses a discriminative model to relabel unsuccessful sequences of states, by generating instructions in hindsight. A similar idea had been implemented with HIGHER [9], a method that learns this function from data labeled by the sparse reward. Positive samples, where the trajectory coincides with proposed instruction, are used for training the model next to the policy. However, their implementation is not publicly available, and the architecture described in their paper is limited to the 2D MiniGrid environment BabyAI [14]. Another limitation is their focus on single transitions rather than the full trajectory. We address this shortcoming with our seq2seq model [22] HIPSS, that predicts instructions based on sequences of states while also being available to the public.⁠¹

Fig. 2 depicts the architecture of HIPSS and Algorithm 1 describes the learning procedure in pseudocode.

Figure 2: HIPSS model architecture. Both the encoder and decoder are multi-layered gated recurrent units [23].

The objective of HIPSS is not enforcing to learn the grammar as we implicitly convey it with our word-based loss, which is sensitive to their particular positions in the

⁠¹Available at https://github.com/knowledgetechnologyuhh/hipss
instruction. Formally, we train the model to estimate the conditional probability of words, given the trajectory of states seen in Equation 3. Here, $h$ represents the context (output of the encoder in Figure 2) which the decoder uses to autoregressively generate the instruction.

$$p(w_1, \ldots, w_N | s_0, \ldots, s_t) = \prod_{i=1}^{N} p(w_i | h, w_1, \ldots, w_{i-1}) \quad (3)$$

Each word prediction is a distribution over all the words of our known task-specific vocabulary.

**Algorithm 1 HIPSS**

$\pi_\theta$ policy $M_\phi$ HIPSS model
$B$ replay buffer $D$ HIPSS dataset

1: for episode $i = 0 \ldots M$ do
2: Sample initial state $s_0$ and episodic goal $g_i^1$
3: for time step $t = 0 \ldots T$ do
4: Sample action $a_t \sim \pi_\theta(s_t, g_i^t)$
5: Take environment step $s_{t+1} \sim p(s_{t+1} | s_t, a_t)$
6: Calculate reward $r_t \leftarrow R_g(s_{t+1}, g_i^t)$
7: end for
8: if $r_t = 0$ then
9: Store successful trajectory $D \leftarrow D \cup (s_{<t}, g_i^t)$
10: else if $r_t = -1$ and interplay with wrong object then
11: Replace $g_i^t$ with predicted goal $\hat{g}_i^t \leftarrow M_\phi(s_{<t})$
12: end if
13: Store transitions $B \leftarrow B \cup \{(s_t, a_t, r_t, s_{t+1}, g_i^t)\}_{t=0}^{T}$
14: Update $\pi_\theta$ with mini-batch from $B$
15: Update $M_\phi$ with mini-batch from $D$
16: end for

**C. Summary**

With Figure 3, we depict the outcome-related mechanisms that are triggered for both methods HEIR and HIPSS, showing the similarities but also their differences in terms of the origin of their hindsight instructions. While HEIR requires the synthetic social partner [4] to provide the instructions in hindsight, HIPSS exploits the sparse reward from Equation 2 to collect positive training samples and to predict instructions by itself [9]. In the following Section V, we consider both approaches stand-alone.

**V. EXPERIMENTS**

**A. Environment**

As of now, there is a lack of environments allowing low-level control in a robotic setup while providing hindsight instructions. To address this, we present our language-focused learning environment LANRO as a testbed for grounded language learning.\(^2\) In all tasks, we leverage a Franka Emika Panda robot with 7-DOF simulated by the PyBullet physics engine [25]. Following, we describe the essential components of our open-source learning platform.\(^3\)

\(^2\)LANRO got inspired by the implementation of panda-gym [24]
\(^3\)Available at https://github.com/knowledgetechnologyuhh/lanro-gym

**B. Task description**

For this paper, we consider the reach task, where we instruct the robot to reach one out of two objects in a scene (cf. Figure 1). The environment’s collision detection evaluates the task-condition as true, when the robot slightly touches the correct object without causing a too large positional change to the goal and non-goal objects. To study our implementations, we
utilize 4 modes to expand the space of instructions with respect to the number of color and shape words, while employing the verbs reach, touch and contact:

1) **Default**: Instructions are generated based on a selection of 3 colors, red, green, and blue. This option only contains objects of type box. To expand the space of possible instructions, we use the 3 shape-specific words box, block, and square, although the goal object could be identified by its color only.

2) **Color**: We expand the selection of colors by yellow, purple, orange, magenta, cyan, and brown, making the task more challenging while keeping the single shape.

3) **Shape**: We expand the Default mode by a rectangle and cylinder, adding the shape-specific words, rectangle, oblong and brick, and cylinder, barrel, and tophat respectively.

4) **ColorShape**: We combine the richness of colors from Color with the diversity of objects from Shape, to create our most demanding setup.

In Table I, we provide an overview of the task modes with their total number of unique instructions the agent observes.

**TABLE I**: The table lists the number of colors and shapes with the resulting number of total instructions per task mode.

| Mode     | #colors | #shapes | #instructions |
|----------|---------|---------|---------------|
| Default  | 3       | 1       | 9             |
| Color    | 9       | 1       | 27            |
| Shape    | 3       | 3       | 27            |
| ColorShape| 9      | 3       | 81            |

**C. Replay Strategy for Hindsight Instruction Replay**

Like the authors of HER [7], we empirically explored our 3 replay strategies by running experiments in all the 4 presented task modes of Subsection V-B. The results of Figure 4 show the mean success rate of the presented strategies (Subsection IV-A), with the shaded area as standard error of 3 trials for each configuration.

While one possibly expects the final method to work the best, as it labels the transitions with the expert signal most of the time, the future method performs at least twice as good because it also takes advantage of states reached afterward. The episode strategy performs the worst. A reason for this could be the larger distance in terms of transitions until the hindsight signal appears. All in all, our experiments favor the future strategy, which is in accordance with the findings of the HER paper [7]. In the remainder of this article, we utilized the future strategy to conduct experiments with both methods HEIR and HIPSS.

**D. Language Representations for Hindsight Learning**

For our experiments, we use two methods to represent words as input to the actor and critic network, fed as sequence into a multi-layered gated recurrent unit [23]. We tested one-hot encodings and trainable word embeddings as a lookup table of randomly initialized vectors for each word. Unlike other methods [4], [12], we empirically confirm that learned

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Fig. 4: The figure shows the success rate (y-axis) and the environment steps (x-axis) for the 4 task modes, contrasting the replay strategies future, final, and episode (cf. Subsection IV-A) with HEIR. We consider the states close to an expert signal as valuable, and augment our replay buffer with those relabeled by a sparse reward (0, 0) or a reduced penalty (−0, 9) defined in Subsection IV-A.
embeddings outperform one-hot encodings (see Table II). A possible explanation is that the embeddings capture the semantic similarities and relationship of task-relevant object properties in an end-to-end manner. This is particularly useful for more complex linguistic instructions with several colors and shapes, which our hindsight procedure possibly exploits.

TABLE II: This table showcases the mean episodic success of an agent trained with two different word representations, utilizing our two implementations, HEIR and HIPSS. The used representations are one-hot encodings and learned embeddings.

| Mode       | HEIR one-hot | HEIR learned embeddings | HIPSS one-hot | HIPSS learned embeddings |
|------------|--------------|-------------------------|---------------|--------------------------|
| Default    | 48 ± 0.16    | 82 ± 0.13               | 61 ± 16       | 84 ± 0.13                |
| Color      | 30 ± 0.11    | 41 ± 0.1                | 16 ± 8        | 37 ± 0.12                |
| Shape      | 40 ± 0.18    | 60 ± 0.1                | 60 ± 15       | 66 ± 0.13                |
| Color/Shape| 12 ± 0.05    | 22 ± 5                 | 14 ± 1        | 40 ± 0.11                |

E. Results

Our experiments compare the baseline language-conditioned SAC (LCSAC) to HEIR and HIPSS. In Figure 5, we use the reach task with its 4 levels of difficulty to evaluate the language-conditioned learning capabilities with different amounts of task-relevant properties. While the simple task mode Default in Figure 5a does not convey major improvements except the improved stability in later training stages (around 3,500,000 environment steps), HEIR learns faster within the task Color during the first 500,000 steps, but then the learning performance of our approaches slows down compared to the baseline LCSAC (Figure 5b). In Figure 5c with the mode Shape, HEIR and HIPSS show a better success rate than the baseline. They also indicate more stable learning properties because the deviation of the success rate is lower. However, as illustrated in Figure 5d, the most difficult task mode Color/Shape shows other results. The synthetic predictions generated with HEIR seem not to improve the learning compared to LCSAC. However, we observe major advantages when using HIPSS. It converges to a success rate of around 0.65, whereas the success rate of the baseline reaches 0.4 and HEIR reaches 0.3.

We provide all the hyperparameters and single script to replicate the experimental results in our GitHub repository (cf. Subsection IV-B).

VI. Discussion

Our results show that self-predicted instructions with HIPSS improve the training performance and overall success rate. This is particularly surprising if we combine the data of Figure 5 with the considerations in Table I, which shows the linguistic complexity of the task modes: it indicates that our HIPSS method provides the largest performance gain for the most difficult task modes.

In the progress of training, the success rate rises and the policy makes fewer and fewer mistakes, which decreases the hindsight instruction generation.

Fig. 5: The figure shows the success rate (y-axis) and the environment time steps (x-axis) for the baseline LCSAC, HEIR, and HIPSS. Each configuration consists of 5 trials, with the shaded area being the standard error and the solid line the mean. We see performance gains for both hindsight methods in Figure 5c, better convergence behavior for HIPSS in Figure 5a and a better performance on average for the hardest setup in Figure 5d.
While HEIR is faster than HIPSS in the early stages of training (cf. Figure 5b and Figure 5d), HIPSS outperforms it in almost all cases later on. A possible explanation for the superior performance of the predicted instructions of HIPSS over the synthetic instructions of HEIR is that the predicted instructions are more diverse than the expert instructions, and sometimes even incorrect. Therefore, they might alleviate the issue of hindsight bias, which Bai et al. [26] formulate as difference between the likelihoods of collected episodes conditioned on different goals. In other words, we assume that the policy generates a similar trajectory under the hindsight instruction $\hat{g_t}$, which is not necessarily true because a different instruction $g_t$ was initially given. More precisely, the policy understood the instruction correctly, but performed the wrong action-selection, instead of misunderstanding the instruction but performing correctly. In the former case, providing a hindsight instruction and a sparse reward perturbs the learning greatly (cf. HEIR in Figure 5d). An additional explanation of the performance difference is that the validation accuracy of our HIPSS model is not at 100%, but in the range of 70–85% (depending on the task mode, see Figure 6). This adds noise to the training and improves the policy’s robustness, as also observed in related research [9], [17]. In Figure 6, we underpin this claim by plotting the training and validation accuracy of our HIPSS model for each task mode. We employ a 1 to 5 ratio to store samples inside the training- and validation dataset. This decision is made at the end of each successful episode (cf. Figure 3).

VII. CONCLUSION

In this paper, we present three methods to improve the sample-efficiency in language-conditioned reinforcement learning for robotics. Our first contribution is HEIR, a mechanism for hindsight expert instruction replay. Secondly, HIPSS, a seq2seq model for hindsight instruction prediction, trained with trajectories collected during training only. And finally, we present a class of language-focused tasks implemented with synthetic expert capabilities as part of our environment LANRO. Our results indicate that the self-predicted instructions provide the best performance gain, especially for difficult tasks. In this article, we tested four different command modes. To further underpin our research, we plan to extend our work to real robots, e.g., our humanoid NICO robot [27], [28] and a more diverse collection of simulated environments. Furthermore, we consider a joint architecture to combine the benefits of both approaches as future work, where one uses HEIR to accelerate the early training stages, followed by hindsight replay with HIPSS.

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Fig. 6: We visualize both the training- and validation accuracy of our HIPSS model in all task modes. In the first three modes (Figure 6a, Figure 6a, and Figure 6c), the seq2seq exceeds the word-level accuracy of 80%. However, in the most demanding setup (Figure 6d), the accuracy is distinctly lower due to the larger number of possible instructions and combinations of object properties (cf. Table I).
