Abstract

Autonomous reinforcement learning agents must be intrinsically motivated to explore their environment, discover potential goals, represent them and learn how to achieve them. As children do the same, they benefit from exposure to language, using it to formulate goals and imagine new ones as they learn their meaning. In our proposed learning architecture (IMAGINE), the agent freely explores its environment and turns natural language descriptions of interesting interactions from a social partner into potential goals. IMAGINE learns to represent goals by jointly learning a language model and a goal-conditioned reward function. Just like humans, our agent uses language compositionality to generate new goals by composing known ones. Leveraging modular model architectures based on deepsets and gated attention mechanisms, IMAGINE autonomously builds a repertoire of behaviors and shows good zero-shot generalization properties for various types of generalization. When imagining its own goals, the agent leverages zero-shot generalization of the reward function to further train on imagined goals and refine its behavior. We present experiments in a simulated domain where the agent interacts with procedurally generated scenes containing objects of various types and colors, discovers goals, imagines others and learns to achieve them.

1. Introduction

Building machines that can autonomously discover and learn a variety of skills is a long-standing goal in Artificial Intelligence. One way to address this is to draw inspiration from the way children learn: generating their own goals without relying on externally provided reward functions. As autonomous agents, children explore their environment, discover interesting interactions and turn them into potential goals. They must concurrently learn how to represent goals, select which ones to pursue, learn to tell whenever one is reached and learn how to achieve them. Key mechanisms in such exploration are intrinsic motivations: specific brain mechanisms that trigger spontaneous exploration for the mere purpose of experiencing novelty, surprise or learning progress (Kaplan & Oudeyer, 2007; Kidd & Hayden, 2015).

Algorithmic models of intrinsic motivation were successfully used in developmental robotics (Oudeyer et al., 2007; Baldassarre & Miorilli, 2013) and more recently in deep Reinforcement Learning (deep RL) (Bellemare et al., 2016; Pathak et al., 2017). Intrinsically Motivated Goal Exploration Processes (IMGEP) in particular, enable agents to pursue their own goals without external rewards (Baranes & Oudeyer, 2013; Forestier & Oudeyer, 2016; Forestier et al., 2017), and can be formulated within the deep RL framework (Nair et al., 2018; Colas et al., 2019a; Pong et al., 2019). A major difficulty of such approaches is to represent goal spaces and goal-achievement functions. Previous works usually require hand-crafted definitions, while some use Variational Auto-Encoders (Laversanne-Finot et al., 2018; Nair et al., 2018) to learn image-based goal representations. Moving beyond within-distribution goal generation, out-of-distribution goal generation could power creative exploration in agents, a challenge that remains to be tackled.

In this difficult task, children leverage the properties of language. Language enables them to assimilate thousands of years of experience, embedded in their culture, in only a few years (Tomasello, 1999; Bruner, 1991). As they discover language, their goal-driven exploration changes. Piaget (1926) first described this as a form of private or egocentric speech where children narrate their ongoing activities. Later, Vygotsky (1978) realized that children were not simply narrating what they were doing but rather generating novel plans and goals by using the expressive generativity of language. Interestingly, this generative capability can push the limits of the real, as illustrated by Chomsky (1957)s famous example of a sentence that is syntactically correct but semantically original Colorless green ideas sleep furiously. Language can thus be used to generate out-of-distributions goals by leveraging compositionality to imagine new goals from known ones.
This paper presents **Intrinsic Motivations And Goal INvention for Exploration (IMAGINE)**: a learning architecture which leverages natural language (NL) interactions with a descriptive social partner (SP) to explore procedurally-generated scenes and interact with objects. IMAGINE discovers meaningful environment interactions through its own exploration (Fig. 1a) and episode-level NL descriptions provided by SP (1b). These descriptions are turned into targetable goals by the agent (1c), who learns to represent them by jointly training a language model mapping NL to goal embeddings, as well as a goal-conditioned reward function (1d). The latter provides training signals for policy learning (ticks in Fig.1d,e). More importantly, IMAGINE can generate new goals by composing known ones, and trains on them autonomously via internal signals (1f).

**Related work** - The idea that language understanding is grounded in one’s experience of the world and should not be secluded from the perceptual and motor systems has a long history in Cognitive Science (Glenberg & Kaschak, 2002; Zwaan & Madden, 2005). This vision was transposed to intelligent systems (Steels, 2006; McClelland et al., 2019), applied to human-machine interaction (Dominey, 2005; Madden et al., 2010), semantic representations (Silberer & Lapata, 2012) and recently to deep RL via frameworks such as the BabyAI platform (Chevalier-Boisvert et al., 2019).

In their review on *RL algorithms informed by NL*, Luketina et al. (2019) distinguish between *language-conditional* problems where language is required to solve the task and *language-assisted* problems where language is a supplementary help. In the first category, most works propose instruction-following agents (R. K. Branavan et al., 2010; Chen & Mooney, 2011; Bahdanau et al., 2019; Jiang et al., 2019; Goyal et al., 2019). Conversely, our system is never given any instruction or reward as it sets its own goals and learns its own internal reward function. Bahdanau et al. (2019) learn a reward function jointly with the action policy but does so using an external expert dataset whereas our agent uses trajectories collected through its own exploration. Lastly, Fu et al. (2019) use an inverse RL approach to learn a reward function but require known environment dynamics.

The idea that agents can formulate and imagine new goals by composing language tokens draws its inspiration from the systematic generalization capabilities of grounded language models. **Systematic generalization** (Bahdanau et al., 2018; Hill et al., 2019) refers to generalizations of the type grow any animal + grasp any plant → grow any plant. Although testing sentences are generated following the same composition rules as training sentences, they extend beyond the training distribution. Recent works show that different forms of generalization can emerge. For instance, Hill et al. (2019) study models that can generalize over instructions dealing with basic object concepts (color and shape) but also over instructions referring to motor predicates such as put or lift. Similarly, Hermann et al. (2017) show that language-guided agents can learn relational concepts like the notion of inter-object proximity.

Systematic generalization assumes environments where objects share a common set of properties: e.g. each object has a type, a color, a size, etc. In contrast with works mentioned above, we directly encode that assumption into our models, by representing objects as *single-slot object files*.
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(Green & Quilty-Dunn, 2017): separate entities characterized by a common set of properties. Because all objects are represented in the same way, we propose object-wise-permutation-invariant architectures based on DEEP SET networks (Zaheer et al., 2017).

Contributions - This paper introduces:

1. A learning architecture (IMAGINE) which enables intrinsically motivated agents to acquire repertoires of skills without external rewards, by leveraging NL descriptions of trajectories at the episode level.
2. Goal imagination: agents can leverage the compositional properties of language to imagine new goals and train on them using generalization properties of the reward function and policy.
3. Modular policy and reward function architectures combined with attention mechanisms.
4. Playground: a procedurally generated environment designed to study several types of generalization (across predicates, attributes, object types and categories).
5. A complete study of IMAGINE investigating: 1) the impact of models design choices (Section 3.1), 2) effects of goal imagination (3.3), 3) generalization abilities (3.2) and 4) reliance on social interactions (3.4).

2. Methods

2.1. Problem Definition and Environment

Problem definition - The agent evolves in the environment without any prior on the set of achievable goals and without externally-provided reward functions. The only source of guidance comes from a social partner (SP), an entity providing NL descriptions of relevant interactions achieved at the end of each episode. Descriptions from SP are turned into targetable goals by the agent. The set of achievable goals (G^A) is partitioned into training (G^train) and testing (G^test) sets such that G^train \cap G^test = \emptyset. SP only provides descriptions related to G^train. In addition, goals imagined by the agent belong to a third set called imagined set (G^im = Imagination(G^train)) that intersects with G^test. The set of all expressible goals is G^NL (see Venn diagram in Supplementary Fig. 11). In this setting, the learning architecture must maximize its average competence on G^A = G^train \cup G^test. A successful agent discovers and masters all training goals, further expands its skills by training on imagined goals, and generalizes on testing goals.

Environment - The Playground environment is a continuous 2D world. In each episode, N = 3 objects are uniformly sampled from a set of 32 different object types (e.g. dog, cactus, sofa, water, etc.), organized into 5 categories (animals, furniture, plants, etc.) (see Fig. 1). Sampled objects have a color (R,G,B) and can be grasped. Animals and plants can be grown when the right supplies are brought to them (food or water for animal, water for plants), whereas furniture cannot (e.g. sofa). Random scene generations are conditioned by the goals selected by the agent (e.g. grasp red lion requires the presence of a red lion).

Agent embodiment - In this environment, the agent can perform bounded continuous translations in the 2D plane, grasp and release objects by changing the state of its gripper. It perceives the world from an allocentric perspective and thus has access to the whole scene.

Agent perception - The scene is described by a state vector containing information about the agent’s body and the N objects. Each object is represented by a set of features describing its type (one-hot encoding of size 32), its 2D-position, color (RGB code), size (scalar) and whether it is grasped (boolean). Categories are not explicitly encoded. Color, size and initial positions are sampled from uniform distributions making each object unique. At time step t, we can define an observation o_t as the concatenation of body observations (2D-position, gripper state) and objects’ features. The state s_t used as input of the models is the concatenation of o_t and Δo_t = o_t - o_0.

Social partner - Part of the environment, SP is implemented by a hard-coded function taking the final state of an episode (s_T) as input and returning NL descriptions of s_T: D_{SP}(s_T) ⊂ D^{SP}. We assume 3 properties for the SP strategy. Precision: descriptions provided by SP are always true. Exhaustiveness: SP provides all verified descriptions for each s_T. Full-presence: SP is always present. Section 3.4 investigates relaxations of the last two assumptions. When SP provides descriptions, the agent hears targetable goals. This mapping D^{SP} → G^train simply consists in removing the first you token (e.g. turning you grasp red door into the goal grasp red door). Given the set of previously discovered goals (G^d) and new descriptions D_{SP}(s_T), the agent infers the set of goals that were not achieved: G^na(s_T) = G^d \ D^{SP}(s_T), where \ indicates complement.

Grammar - We define a grammar to generate achievable goals (G^A), and thus corresponding descriptions:

1. Go: (e.g. go bottom left)
   - go + zone
2. Grasp: (e.g. grasp red cat, grasp any blue thing)
   - grasp + color \cup \{any\} + object type \cup object category
   - grasp + any + color + thing
3. Grow: (e.g. grow green animal, grow any red thing)
   - grow + color \cup \{any\} + living thing \cup \{living thing, animal, plant\}
   - grow + any + color + thing

Bold and \{\} represent sets of words while italics represents specific words. zone includes words referring to areas of the
scene (e.g. top, right, bottom left), object type is one of 32 object types (e.g. parrot, cactus) and object category one of 5 object categories (living thing, animal, plant, furniture, supply). living thing refers to any plant or animal word, color is one of blue, green, red and any refers to any color, or any object. The grammar is detailed in Supplementary Section 5, training and testing sets of goals are defined in Section 2.3. In total, there are 256 achievable goals, corresponding to an infinite number of scenes.

2.2. Architecture

![Diagram of IMAGINE architecture]

Figure 2. The IMAGINE architecture. Colored boxes represent the different modules composing IMAGINE. Lines represent update signals (dashed) and function outputs (plain). $\mathcal{LM}$ is shared.

Figure 2 represents the IMAGINE architecture whose logic can be outlined as follows:

1. The Goal Generator samples a target goal $g_{\text{target}}$ from discovered and imagined goals ($\mathcal{G}_d \cup \mathcal{G}_\text{im}$).
2. The agent interacts with the environment (RL Agent) using its policy $\Pi$ conditioned by $g_{\text{target}}$.
3. The state-action trajectories are stored in $\text{mem}(\Pi)$.
4. SP observes $s_T$ and provides descriptions $\mathcal{D}_\text{SP}(s_T)$ that the agent turns into targetable goals $G_{\text{SP}}(s_T)$.
5. $\text{mem}(\mathcal{R})$ stores positive pairs $(s_T, G_{\text{SP}}(s_T))$ and infers negative pairs $(s_T, G_{\text{na}}(s_T))$.
6. The agent then updates:
   - Goal Generator: $G_d \leftarrow G_d \cup G_{\text{SP}}(s_T)$ and if allowed to imagine new goals: $G_{\text{im}} \leftarrow \text{Imagination}(G_d)$.
   - Language Model ($\mathcal{LM}$) and Reward Function ($\mathcal{R}$): updated using data from $\text{mem}(\mathcal{R})$.
   - RL agent (actor and critic): A batch of state-action transitions $(s, a, s')$ is sampled from $\text{mem}(\Pi)$. Then Hindsight Replay and $\mathcal{R}$ are used to select goals to train on and compute rewards $(s, a, s, g_{\text{NL}}, r)$. Finally, the policy and critic are trained via RL.

The next paragraphs describe each module. Further implementation details, training schedules and pseudo-code can be found in the Supplementary Section 6.

**Language model** - The language model ($\mathcal{LM}$) embeds NL goals ($\mathcal{LM}(g_{\text{NL}}): \mathcal{G}^{\text{NE}} \rightarrow \mathbb{R}^{100}$) using an LSTM (Hochreiter & Schmidhuber, 1997) trained jointly with the reward function. The reward function, policy and critic become language-conditioned functions when coupled with $\mathcal{LM}$, which acts like a goal translator.

**Reward function** - Learning a goal-conditioned reward function ($\mathcal{R}$) is framed as a binary classification. The reward function maps a state $s$ and a goal embedding $g = \mathcal{LM}(g_{\text{NL}})$ to a binary reward: $\mathcal{R}(s, g): S \times \mathbb{R}^{100} \rightarrow \{0, 1\}$.

**Architecture** - The reward function, policy and critic leverage modular architectures inspired by DEEP SET (Zaheer et al., 2017) combined with gated attention mechanisms (Chaplot et al., 2017). DEEP SET is a network architecture implementing set functions (input permutation invariance). Each input is mapped separately to some (usually high-dimensional (Wagstaff et al., 2019)) latent space using a shared network. These latent representations are then passed through a permutation-invariant function (e.g. mean, sum) to ensure the permutation-invariance of the whole function. In the case of our reward function, inputs are grouped into object-dependent sub-states $s_{\text{obj}}(i)$, each mapped to a probability $p_i$ by a same network $\text{NN}^R$ (weight sharing). $\text{NN}^R$ can be thought of as a single-object reward function which estimates whether object $i$ verifies the goal ($p_i > 0.5$) or not. Probabilities $[p_i]_{i \in [1..N]}$ for the $N$ objects are then mapped into a global binary reward using a logical OR function: if any object verifies the goal, then the whole scene verifies it. This OR function implements object-wise permutation-invariance. In addition to object-dependent inputs, the computation of $p_i$ integrates goal information through a gated-attention mechanism. Instead of being concatenated, the goal embedding $g$ is cast into an attention vector $\alpha^g$ before being combined to the object-dependent sub-state through an Hadamard product (term-by-term) to form the inputs of $\text{NN}^R$: $x^g_i = s_{\text{obj}}(i) \odot \alpha^g$. This can be seen as scaling object-specific features according to the interpretation of the goal $g_{\text{NL}}$. Finally, we pre-trained a neural-network-based OR function: $\text{NN}^{\text{OR}}$ such that the output is 1 whenever $\max_i([p_i]_{i \in [1..N]}) > 0.5$. This is required to enable end-to-end training of $\mathcal{LM}$ and $\mathcal{R}$. The overall function can be expressed by:

$$\mathcal{R}(s, g) = \text{NN}^{\text{OR}}([\text{NN}^{R}(s_{\text{obj}}(i) \odot \alpha^g)]_{i \in [1..N]})$$

We call this architecture $\text{MA}$ for modular-attention. Implementation details and a representation of this architecture can be found in Supplementary Section 6.2.1 and Fig. 8c).

**Data** - Interacting with the environment and SP, the agent builds a dataset of entries $[s_T, g_i, r_i = 1, \forall g_i \in G_{\text{SP}}(s_T)$ and $s_T, g_i, r_i = 0, \forall g_i \in G_{\text{na}}(s_T)$ where $r_i$ is a binary reward marking the achievement of $g_i$ in state $s_T$. $\mathcal{LM}$ and $\mathcal{R}$ are periodically updated by backpropagation on this dataset.
Multi-goal RL agent - Our agent is controlled by a goal-conditioned policy $\Pi$ that leverages an adapted modular-attention (MA) architecture (see Supplementary Fig. 10). Similarly, the goal embedding $g$ is cast into an attention vector $\beta^g$ and combined with the object-dependent sub-state $s_{obj(i)}$ through a gated-attention mechanism. As usually done with DEEP SET, these inputs are projected into a high-dimensional latent space (of size $N \times \text{dim}(s_{obj(i)})$) using a shared network $\text{NN}^H$ before being summed. The result is finally mapped into an action vector $a$ with $\text{NN}^\text{action}$. Following the same architecture, the critic computes the action-value of the current state-action pair given the current goal with $\text{NN}^\text{action-value}$:

$$
\Pi(s, g) = \text{NN}^\text{action} \left( \sum_{i \in [1..N]} \text{NN}^H (s_{obj(i)} \odot \beta^g) \right),
$$

$$
Q(s, a, g) = \text{NN}^\text{action-value} \left( \sum_{i \in [1..N]} \text{NN}^Q (s_{obj(i)}, a) \odot \gamma^g) \right).
$$

Critic and policy are trained using Deep Deterministic Policy Gradient DDPG (Lillicrap et al., 2015), although any other off-policy algorithm could be used.

Hindsight learning - Our agent uses hindsight learning, which means it can replay the memory of a trajectory (e.g. when trying to grasp object A) by pretending it was targeting a different goal (e.g. grasping object B) (Andrychowicz et al., 2017; Mankowitz et al., 2018; Colas et al., 2019a). In practice, goals originally targeted during data collection are replaced by others in the batch of transitions used for RL updates, a technique known as hindsight replay (Andrychowicz et al., 2017). To generate candidate substitute goals, we use the reward function to scan a list of 50 goals sampled randomly so as to bias the ratio of positive examples.

Goal generator - The goal generator is a generative model of NL goals. Generated goals are used to serve as targets during environment interactions and as substitute goals for hindsight replay. When goal imagination is disabled, the goal generator samples uniformly from the set of discovered goals $G_d$. When enabled, it uses a simple heuristic leveraging the compositional nature to imagine new goals from a set of known ones $G_{im} = \text{Imagination}(G_d)$ and then samples goals from $G_d$ with $p = 0.5$ and $G_{im}$ with $p = 0.5$. The heuristic consists in computing sets of equivalent words: words that appear in two sentences that have an editing distance of 1 at the word-level (i.e. sentences that differ by one word). For example, having discovered grasp red lion and grow red lion, grasp and grow are considered equivalent and the goal grow green tree can be generated from the known one grasp green tree (see Fig. 1f). The pseudo-code and a description of all imaginable goals are provided in Supplementary Section 6.3. The agent can generate goals from $G_{\text{train}}$ before they have been discovered. For others, the agent cannot rely on any descriptions from SP.

2.3. Testing Goal Generalization

We define 5 different types of out-of-distribution generalization:

- **Type 1 - Attribute-object generalization:** predicate + \{blue door, red tree, green dog\}. Understanding grasp red tree requires to leverage knowledge about the red attribute (grasping red non-tree objects) and the tree object type (grasping non-red tree objects).
- **Type 2 - Attribute extrapolation:** predicate + color $\cup$ \{any\} + flower. As flower is removed from the training set, grasp red flower requires the extrapolation of the red attribute to a new object type.
- **Type 3 - Predicate-category generalization:** grasp + color $\cup$ \{any\} + animal. Understanding grasp any animal requires to understand the animal category (from growing animal and growing animal objects) and the grasp predicate (from grasping non-animal objects) to transfer the former to the latter.
- **Type 4 - Easy predicate-object generalization:** grasp + color $\cup$ \{any\} $\cup$ \{fly\}. Understanding grasp any fly requires to leverage knowledge about the grasp predicate (grasping non-fly objects) and the fly object (growing flies).
- **Type 5 - Hard predicate-object generalization:** grow + color $\cup$ \{any\} $\cup$ plant $\cup$ \{plant, living\_thing\}. grow any plant requires to understand the grow predicate (from growing animals) and the plant objects (and category) (from grasping plant objects). However, this transfer is more complex than the reverse transfer in Type 4 for two reasons. First, the interaction modalities vary: plants only grow with water. Second, Type 4 is only about the fly object, while here it is about all plant objects and the plant and living\_thing categories.

Each of the testing goals described above is removed from the training set ($G_{\text{train}} \cap G_{\text{test}} = \emptyset$, see Supplementary Table 1 for the complete list of testing goals). The agent can generalize to out-of-distribution goals in three different ways. When tested on a goal from $G_{\text{test}}$ that was never encountered before, the policy may readily achieve it (policy zero-shot generalization). Its reward function may also promptly tell whether the goal is achieved or not (reward zero-shot generalization). Finally, when allowed to train on imagined goals, an agent can use reward zero-shot generalization to fine-tune its policy so as to improve on the initial policy zero-shot generalization (necessary in Type 5). We call this fine-tuning policy n-shot generalization because the agent is still tested on a goal that was never mentioned by SP (not associated with any external signal).
3. Experiments and Results

We conduct a set of experiments to assess the properties of IMAGINE. In Section 3.1, we justify implementation choices and analyze IMAGINE's performance on $G^{train}$. Then, we study generalization properties (Section 3.2). We further investigate the effects of goal imagination on exploration and n-shot generalization (Section 3.3). Finally, we look at IMAGINE robustness when assumptions about SP’s strategy are relaxed (Section 3.4). Training performances are evaluated using average success rates ($\overline{SR}$) for policy learning, and $F_1$-score for reward learning. They are computed across goals, SR goal-specific measures being estimated over 30 evaluation episodes. Note that these are called training performances because they use training goals from $G^{train}$, but they do assess generalization to new states because scenes are generated procedurally. Agents were also tested in confusing settings, without significant effect on performance (see Supplementary Section 7.6). We always provide the mean and standard deviation over 10 seeds, and report statistical significance using a two-tail Welch’s t-test at level $\alpha = 0.05$ as advised in Colas et al. (2019b) (noted by star and circle markers on figures). Additional results are presented in the Supplementary and include reward function and circle markers on figures). Additional results are presented in the Supplementary and include reward function performance along RL training, visualization of goal embeddings, and additional exploration metrics (see Supplementary Sections 7.2 to 7.5 respectively). In the next two sections, agents cannot imagine goal.

3.1. Learning Reward Function and Policy

Supervised learning of the reward function - We train the reward function in a supervised setting independently from the policy. As episodes collected with a random action policy do not contain sufficient positive examples, we use data collected through an RL policy co-trained with a reward function (see Supplementary Fig. 9). Figure 3a shows that our proposed architecture (MA, left) achieves near-perfect $F_1$-score on $G^{train}$ (grey). Thus, all following experiments use MA reward functions.

Pre-trained vs co-learning - Figure 3b compares training and testing $\overline{SR}$ for the policy MA architecture and an oracle variant using a pre-trained reward function (MA-PR). As using ground truth rewards makes the algorithm approximately $18 \times$ slower (because it cannot parallelize evaluations across multiple goals), we use the near-perfect reward functions trained in supervised settings to provide oracle rewards. MA reaches performance comparable to MA-PR, even though the latter benefits from an immediate understanding of goal achievements from the moment they are discovered.

Architecture comparisons - We compare MA to two competing architectures: 1) flat-concatenation (FC) where the goal embedding is concatenated to the observation and 2) flat-attention (FA) where the gated attention mechanism is applied at the state-level rather than at the object-dependent sub-state level (see Supplementary Section 6.2.1 and Supplementary Figures 8a and 8b for details). As shown in Figures 3a and 3b, our proposed architecture greatly outperforms competitors in terms of training and zero-shot generalization (testing performance) for both reward function and policy learning. Modular architectures reduce the number of parameters to optimize and, by enforcing object-wise permutation invariance, lead to more efficient learning. In addition, the gated-attention mechanism improves model interpretability (see Supplementary Section 7.4).

3.2. Generalizations

MA models demonstrate good zero-shot generalizations of Type 1 (attribute-object generalization, e.g. grasp red tree), Type 3 (predicate-category generalization, e.g. grasp any
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3.3. Goal Imagination

Agents are now allowed to perform goal imagination phases during training, which implements the full version of IMAGINE. In the goal imagination phase, agents can generate and train on imagined goals, while SP continues to describe interactions related to $G^{\text{train}}$.

Imagination of meaningful goals Setting aside goals already found in $G^{\text{train}}$, 41.2% of the imagined goals computed from $G^{\text{train}}$ are achievable ($G^{\text{im}} \cap G^{A}$) and cover 87.5% of $G^{\text{test}}$, (see in Supplementary Venn diagram 11 and Table 2). The goals containing the word flower could not be generated, as SP never uses it. Among unfeasible goals (e.g. go right left), some still make sense: e.g. grow blue door. When attempting to perform goals of the form grow + color $\cup \{\text{any}\}$ + furniture, the agent demonstrates interesting behaviors, bringing water or food to the corresponding furniture just like it would do to grow an animal (occurrence rate of 35%).

Effects on the learning trajectory Goal imagination does not significantly impact performance on $G^{\text{train}}$ ($p$-values > 0.05 except in a few points) but does impact generalization and exploration. Figure 4a shows the $\mathcal{SR}$ on the set of testing goals, when the agent starts imagining new goals early (after $6 \times 10^3$ episodes), half-way (after $48 \times 10^3$ episodes) or when not allowed to do so. Imaging goals leads to significantly improved generalization at convergence (Fig. 4a). Figure 5 shows the rarity-weighted interesting interaction count exploration score ($RW-I^2C$) computed on the testing set as:

$$RW-I^2C_{\text{test}} = \frac{1}{\delta_{t}1/c_{i}} \sum_{i \in \mathcal{I}} \sum_{t=1}^{600} \delta_{i,t}$$

where $\mathcal{I}$ is a set of interesting interactions performed during the last 600 episodes (here $\mathcal{I} = G^{\text{test}}$). $\delta_{i,t} = 1$ when interaction $i$ is achieved at the end of episode $t$ and $c_{i}$ is the number of times interaction $i$ has been achieved since the first episode, $1/c_{i}$ measuring rarity. The $RW-I^2C_{\text{test}}$ metric and others computed on different sets of interactions (including non-goal interactions) demonstrate a significant impact of goal imagination on the exploration of the environment and its possible interactions, beyond interactions relevant for SP (see Fig. 5 and Supplementary Section 7.5).

Effect on policy n-shot generalization Evaluating the agent on $G^{\text{test}}$ before goal imagination boils down to testing the policy zero-shot generalization. In the second phase, the agent can imagine, target and train on new goals (Fig. 4b).

Figure 5. Goal imagination and exploration. Stars indicate significant differences w.r.t the never condition.

Figure 4. Goal imagination. Vertical dashed lines mark the start of goal imagination. a: $\mathcal{SR}$ on testing set. b: $\mathcal{SR}$ on testing set for the 5 generalization types when the agent starts imagining goals half-way through learning. c: Behavioral adaptation, empirical probabilities that the agent brings supplies to a plant when trying to grow it. Stars indicate significance (a: tested against never).
Assuming the agent discovered all goals from $G_{\text{train}}$, these imagined goals include all but Type 2 testing goals. Thus, evaluating goal-imagining agents on Types 1,3,4,5 can be seen as testing policy n-shot generalization, as the policy could be updated w.r.t. these testing goals using self-generated rewards. In Type 5—the only type where agents can actually improve—the agent imagines goals of the form $\text{grow} + \text{color} \cup \{\text{any}\} + \text{plant}$. Before goal imagination, the agent generalizes knowledge about how to grow animals to attempt to grow plants, and brings them food or water with equal probability when both are available (Fig. 4c, left). After goal imagination starts (dashed line), the agent can train on such goals and significantly improve on its original zero-shot generalization using current experience. As it trains, the agent displays what we call behavioral adaptation: it learns that only water, not food, should be brought to plants (Fig. 4c, right). That explains the boost in Type 5 generalization performance observed in Figure 4b.

### 3.4. Social Interactions

![Figure 6. Influence of social feedbacks. a: \(ST^R\) on \(G_{\text{train}}\) for some social strategies. Stars indicate significant differences w.r.t. ex:1.0.](image)

We study the relaxation of the full-presence and exhaustiveness assumptions. We first vary the probability of SP being present, while keeping exhaustiveness (ex: $p = [1, 0.5, 0.1, 0.05]$). Then we switch to a non-exhaustive strategy (non-ex) where SP only provides one positive and one negative description per episode (or more positive if new goals are reached). For the non-ex setting, we also vary the probability of presence (see Fig 6). Our learning architecture is robust to non-exhaustiveness and occasional presence. When sufficient data is collected to achieve a good reward function $F_1$-score, the agent can learn autonomously with relatively little social interactions.

### 4. Discussion and Conclusion

IMAGINE is a learning architecture enabling autonomous learning by leveraging NL interactions with a social partner. As other algorithms from the IMGEP family, IMAGINE sets its own goals and builds behavioral repertoires without external rewards. This is done through the joint training of a language model for goal representation and a goal-achievement function to generate internal rewards. Our proposed modular architectures with gated-attention enable efficient out-of-distribution generalization of the reward function and policy, while the ability to imagine new goals by composing known ones leads to improvements over initial generalization abilities and fosters exploration beyond the set of interactions relevant to SP.

Although vision inputs can be considered more general than object features, we know humans encode persistent object representations (Johnson, 2013; Green & Quilty-Dunn, 2017). Our proposed modular-attention model architectures assume such representations to be available and leverage them to enable strong generalization, assumptions that can be relaxed by combining IMAGINE with unsupervised multi-object representation learning algorithms (Burgess et al., 2019; Greff et al., 2019).

IMAGINE does not use externally-provided rewards but learns which interactions are interesting from language-based interactions with a social partner. Descriptions in NL provide an easier way to guide machines towards relevant interactions than the hand-crafting of reward functions. Attention mechanisms further extend the interpretability of the agent’s learning by mapping language to attentional scaling factors (see Supplementary Fig. 15). In addition, Section 3.4 shows that agents can learn to achieve goals from a relatively small number of descriptions, paving the way towards trajectory descriptions provided by real humans.

NL goal imagination presents a natural way to leverage language for the generation of out-of-distribution goals. Coupled with zero-shot generalization properties of the reward function and policy, goal imagination fosters exploration and extends behavioral repertoires beyond what SP knows, enabling true intrinsically motivated exploration and skills collection. Our agent even tries to grow pieces of furniture with supplies, a behavior that can echo the way a child may try to feed his doll.

Further work could investigate more realistic feedback (e.g. unreliable), and new ways for SP to interact with the agent (e.g. guiding attention). The modular architecture being invariant to the number of objects, we could also generate scenes with a variable number of objects. Another improvement could be the generation of goals conditioned on the objects in the scene. This would require a generative model close to the one formulated in Cideron et al. (2019). Finally, off-policy learning (Fujimoto et al., 2018) could be used to reinterpret past experience in the light of new imagined goals without any additional environment interactions.

**Links.** Demonstration videos are available at [https://sites.google.com/view/imagine-drl](https://sites.google.com/view/imagine-drl). Source code has been submitted in the supplementary.
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5. The **Playground Environment**

5.1. Environment description

All positions are constrained within \([-1,1] \times [-1,1]\). The initial position of the agent is \((0,0)\) while the initial object positions are randomized so that they are not in contact \((d(\text{obj}_1, \text{obj}_2) > 0.3)\). Object sizes are sampled uniformly in \([0.2,0.3]\), the size of the agent is 0.05. Objects can be grasped when the agent has nothing in hand, when it is close enough to the object center \((d(\text{agent}, \text{obj}) < (\text{size(agent)} + \text{size(obj)})/2)\) and the gripper is closed \((1, -1\) when open). There are 10 animals, 10 plants, 10 pieces of furniture and 2 supplies. Admissible categories are **animal,** **plant,** **furniture,** **supply** and **living thing** (animal or plant), see Fig. 7. Objects are assigned a color attribute (red, blue or green). Their precise color is a continuous RGB code uniformly sampled from the RGB subspace associated with their attribute color.

- **living thing** = **animal** ∪ **plant**
- **animal** = \{dog, cat, chameleon, human, fly, parrot, mouse, lion, pig, cow\}
- **plant** = \{cactus, carnivorous, flower, tree, bush, grass, algae, tea, rose, bonsai\}
- **furniture** = \{door, chair, desk, lamp, table, cupboard, sink, window, sofa, carpet\}
- **supply** = \{water, food\}
- **predicate** = \{go, grasp, grow\}

From the set of achievable goals generated by this grammar, we select a subset to form a testing set so that \(G^A = G^{\text{train}} \cup G^{\text{test}}\) and \(G^{\text{train}} \cap G^{\text{test}} = \emptyset\). Goals from \(G^{\text{test}}\) are intended to evaluate the generalization abilities of our agent and cannot be used as descriptions by SP. The five different types of generalization we study are detailed in Main Section 2.3. Table 1 provides the exhaustive list of goals in \(G^{\text{test}}\) grouped by generalization types.

| Type 1                                                                 | Grasp blue door, Grasp green dog, Grasp red tree, Grow green dog |
|-----------------------------------------------------------------------|------------------------------------------------------------------|
| Type 2                                                                | Grasp any flower, Grasp blue flower, Grasp green flower, Grasp red flower, Grow any flower, Grow blue flower, Grow green flower, Grow red flower, |
| Type 3                                                                | Grasp any animal, Grasp blue animal, Grow green animal, Grow red animal |
| Type 4                                                                | Grasp any fly, Grasp blue fly, Grow green fly, Grow red fly       |
| Type 5                                                                | Grow any algae, Grow any cactus Grow any bush, Grow any cactus Grow any carnivorous, Grow any grass Grow any living thing, Grow any plant Grow any rose, Grow any tea Grow any tree, Grow blue algae Grow blue bonsai, Grow blue bush Grow blue cactus, Grow blue carnivorous Grow blue grass, Grow blue living thing Grow blue plant, Grow blue rose Grow blue tea, Grow blue tree Grow green algae, Grow green bonsai Grow green bush, Grow green cactus Grow green carnivorous, Grow green grass Grow green living thing, Grow green plant Grow green rose, Grow green tea Grow green tree, Grow green algae Grow red bonsai, Grow red bush Grow red cactus, Grow red carnivorous Grow red grass, Grow red living thing Grow red plant, Grow red rose Grow red tea, Grow red tree |

Figure 7. Representation of possible objects types and categories.
6. Supplementary Methods

6.1. IMAGINE Pseudo-Code

Algorithm 1 outlines the pseudo-code of our learning architecture. See Main Section 2.2 for a detailed explanation of each module and function.

Algorithm 1 IMAGINE

1: Input: env, SP
2: Initialize: \( \mathcal{LM}, \mathcal{R}, \Pi, \text{mem}(\mathcal{R}), \text{mem}(\Pi), \mathcal{G}_d, \mathcal{G}_m \)
   \# Random initializations for networks
   \# empty sets for memories and goal sets
3: for \( e = 1: \text{N}_{\text{episodes}} \) do
4:   if \( \mathcal{G}_d \neq \emptyset \) then
5:     sample \( g_{\text{NL}} \) from \( \mathcal{G}_d \cup \mathcal{G}_m \)
6:     \( g \leftarrow \mathcal{LM}(g_{\text{NL}}) \)
7:   else
8:     sample \( g \) from \( \mathcal{N}(0, I) \)
9:   end if
10: \( s_0 \leftarrow \text{env.reset}() \)
11: for \( t = 1: T \) do
12:   \( a_t \leftarrow \pi(s_{t-1}, g) \)
13:   \( s_t \leftarrow \text{env.step}(a_t) \)
14:   \( \text{mem}_1\text{.add}(s_{t-1}, a_t, s_t) \)
15: end for
16: \( \mathcal{G}_{SP} \leftarrow \text{SP.get.descriptions}(s_T) \)
17: \( \mathcal{G}_d \leftarrow \mathcal{G}_d \cup \mathcal{G}_{SP} \)
18: \( \text{mem}(\mathcal{R})\text{.add}(s_T, g_{\text{NL}}) \) for \( g_{\text{NL}} \) in \( \mathcal{G}_{SP} \)
19: if goal imagination allowed then
20:   \( \mathcal{G}_m \leftarrow \text{Imagination} (\mathcal{G}_d) \) \# see Algorithm 2
21: end if
22: \( \text{Batch}_1 \leftarrow \text{ModularBatchGenerator}(\text{mem}(\Pi)) \)
   \# Batch1=[(s, a, s’)]
23: \( \text{Batch}_1 \leftarrow \text{Hindsight} (\text{Batch}_1, \mathcal{R}, \mathcal{G}_d, \mathcal{G}_m) \)
   \# Batch1=[(s, a, r, g, s’)] where \( r = \mathcal{R}(s, g) \)
24: \( \Pi \leftarrow \text{RL\_Update}(\text{Batch}_1) \)
25: if \( \% \text{reward\_update\_freq} = 0 \) then
26:   \( \text{Batch}_2 \leftarrow \text{ModularBatchGenerator}(\text{mem}(\mathcal{R})) \)
27: \( \mathcal{LM}, \mathcal{R} \leftarrow \text{LM\&RewardFunctionUpdate}(\text{Batch}_2) \)
28: end if
29: end for

6.2. Training details

6.2.1. Supervised Learning of the Reward Function

Reward function inputs - Main Section 2.2 details the architecture of the reward function. The following provides extra details about the inputs. The object-dependent sub-state \( s_{\text{obj}(i)} \) contains information about both the agent’s body and the corresponding object \( i \): \( s_{\text{obj}(i)} = [o_{\text{body}}, \Delta o_{\text{body}}, o_{\text{obj}(i)}, \Delta o_{\text{obj}(i)}] \) where \( o_{\text{body}} \) and \( o_{\text{obj}(i)} \) are body- and object-dependent observations, and \( \Delta o_{\text{body}} = o_{\text{body}}^t - o_{\text{body}}^0 \) and \( \Delta o_{\text{obj}(i)} = o_{\text{obj}(i)}^t - o_{\text{obj}(i)}^0 \) measure the difference between the initial and current observations. The second input is the attention vector \( \alpha^g \) that is integrated with \( s_{\text{obj}(i)} \) through an Hadamard product to form the model input: \( x^g_i = s_{\text{obj}(i)} \odot \alpha^g \). This attention vector is a simple mapping from \( g \) to a vector of the size of \( s_{\text{obj}(i)} \) contained in \([0,1]^{\text{size}(s_{\text{obj}(i)})}\). This cast is implemented by a one-layer neural network with sigmoid activations \( \text{NN}^{\text{cast}} \) such that \( \alpha^g = \text{NN}^{\text{cast}}(g) \).

Architectures - Figure 8c shows a representation of the modular-attention (MA) architecture described in Main Section 2.2. In contrast to MA that deals with a set of object-dependent sub-states, the competing architectures flat-concatenation (FC, Fig. 8a) and flat-attention (FA, Fig. 8b) use a flat representation of the state as input, and combine it with the goal embedding using either concatenation or through gated-attention. They are described below:

- **Flat-concatenation**: the goal embedding \( g \) is simply concatenated with the state vector \( s \) to form the input of a one-hidden-layer network \( \text{NN}^{\text{R}} \) that predicts the reward \( r \).
- **Flat-attention**: the goal \( g \) is cast into an attention vector \( \alpha^g \) of the size of \( s \) via a one-layer network \( \text{NN}^{\text{cast}} \). We perform gated-attention by taking the Hadamard product \( x^g = s \odot \alpha^g \). The vector \( x^g \) is then fed to a one-hidden-layer network \( \text{NN}^{\text{R}} \) that predicts the reward \( r \).

For the three architectures the number of hidden units of the LSTM and the sizes of the hidden layers of fully connected networks are fixed to 100. \( \text{NN} \) parameters are initialized using He initialization (He et al., 2015). The states of the LSTM are initially set to zero. The LSTM’s weights are initialized uniformly from \([-0.1, 0.1]\) and the biases initially set to zero. The LSTM use a \( \text{tanh} \) activation function whereas the \( \text{NN} \) are using ReLU activation functions in their hidden layers and sigmoids at there output.

Training data - The reward function is trained in two contexts. First in a supervised setting to be studied independently from the policy. Second, it is trained in parallel of the policy. To learn a reward function in a supervised setting, we first collected a dataset of \( 50 \times 10^3 \) trajectories and associated goal descriptions using a random action policy. Training the reward function on this data led to poor performances, as the number of positive examples remained low for some goals (see Fig. 9). To pursue the independent analysis of the reward function, we used \( 50 \times 10^3 \) trajectories collected by an RL agent co-trained with its reward function using modular-attention architectures (data characterized by the top distribution in Fig. 9). Results presented in Main Fig. 3a used such RL-collected data. This further advocates for the parallel learning of policy and reward function, as the
policy improves, the quality and diversity of collected trajectories increases, inducing an implicit curriculum for both reward function and policy learning. Furthermore, using a pre-trained reward function for policy learning becomes a cyclical problem, as the pre-training requires data collected by an RL agent. To closely match the training conditions imposed by the co-learning setting, we train the reward function on the final states $s_T$ of each episode and test it on any state $s_t$ for $t = [1, ..., T]$ of other episodes.

**Training schedule** - The architecture are trained via backpropagation using the Adam Optimizer (Kingma & Ba, 2014). The data is fed to the model in batches of 512 examples. Each batch is constructed so that it contains at least one instance of each goal description $g_{NL}$ (all goals in the supervised setting, goals discovered so far in the RL setting). We also use a modular buffer to impose a ratio of positive rewards of 0.2 for each description in each batch. When trained in parallel of the policy, the reward function is updated once every 1200 episodes. Each update corresponds to up to 100 training epochs (100 batches). We implement a stopping criterion based on the $F_1$-score computed from a held-out test set uniformly sampled from the last episodes.

Figure 8. **Reward function architectures.** a: flat-concatenation (FC). b: flat-attention (FA). c: modular-attention (MA).

Figure 9. **Data distributions for the supervised learning of the reward function.** Sorted counts of positive examples per training set descriptions.
(20% of the last 1200 episodes). The update is stopped when the performance on the held-out set does not improve for 10 consecutive training epochs.

6.2.2. Policy Learning Details and Hyperparameters

Architectures - The policy and critic architectures (modular-attention) are described in Main Section 2.2. The policy is represented in Fig. 10, and the critic would be represented by the same figure by simply replacing \( \text{NN}^Q \) by \( \text{NN}^Q \) and \( \text{NN}^\text{action-value} \) by \( \text{NN}^\text{action-value} \). As for the reward function, competing architectures include:

- The flat-concatenation architecture simply concatenates the goal embedding \( g \) and the agent state \( s \) to form the input of the policy, adding actions \( a_t \) to form the input of the critic. These inputs are then mapped with two-hidden-layer networks to actions (policy) or an action-value (critic).
- The flat-attention architecture uses a gated attention mechanism between \( s \) and an attention vector cast from \( g \) before mapping this inputs to actions (policy) or to an action-value (critic) through a two-hidden-layer networks.

In all architectures, we(y) and conduct their own updates independently. Updates are then summed to compute the next set of parameters broadcast to all actors. Each actor is updated for 50 epochs with batches of size 256 every 2 episodes of environment interactions. Using hindsight learning, we enforce a ratio \( p = 0.5 \) of transitions associated with positive rewards in each batch. We use the same hyperparameters as Plappert et al. (2018).

6.3. Goal Imagination

The set of imagined goals is built from the set of training ones as described in Algorithm 2. Figure 11 represents the Venn diagram of the different goal spaces and Table 2 lists all the imagined goals.

Algorithm 2 Goal Imagination. The editing distance between two sentences refers to the number of words to modify to transform one sentence into the other.

1: Input: \( \mathcal{G}_d \) (discovered goals)
2: Initialize: \( \text{word}_eq \) (list of sets of equivalent words, empty)
3: Initialize: \( \text{goal}_\text{template} \) (list of template sentences used for imagining goals, empty)
4: Initialize: \( \mathcal{G}_m \) (empty)
5: for \( g_{\text{NL}} \) in \( \mathcal{G}_d \) do (Computing word equivalences)
6: \( \text{new}_\text{goal}_\text{template} = \text{True} \)
7: \( \text{for } g_m \text{ in } \text{goal}_\text{template} \text{ do} \)
8: \( \text{if } \text{edit}_\text{distance}(g_{\text{NL}}, g_m) == 1 \text{ then} \)
9: \( \text{new}_\text{goal}_\text{template} = \text{False} \)
10: \( w_1, w_2 \leftarrow \text{get_non_matching_words}(g_{\text{NL}}, g_m) \)
11: \( \text{if } w_1 \text{ and } w_2 \text{ not in any of } \text{word}_eq \text{ sets then} \)
12: \( \text{word}_eq.add\{w_1, w_2\} \)
13: \( \text{else} \)
14: \( \text{for } eq\text{-set in word}_eq \)
15: \( \text{if } w_1 \in eq\text{-set or } w_2 \in eq\text{-set then} \)
16: \( eq\text{-set} = eq\text{-set} \cup \{w_1, w_2\} \)
17: \( \text{end if} \)
18: \( \text{end for} \)
19: \( \text{end if} \)
20: \( \text{end if} \)
21: \( \text{end for} \)
22: \( \text{if } \text{new}_\text{goal}_\text{template} \text{ then} \)
23: \( \text{goal}_\text{template}.add(g_{\text{NL}}) \)
24: \( \text{end if} \)
25: \( \text{end for} \)
26: \( \text{for } g \text{ in } \text{goal}_\text{template} \text{ do} \) (Generating new sentences)
27: \( \text{for } w \text{ in } g \text{ do} \)
28: \( \text{for } eq\text{-set in word}_eq \text{ do} \)
29: \( \text{if } w \in eq\text{-set then} \)
30: \( \text{for } w' \text{ in } eq\text{-set do} \)
31: \( g_{im} \leftarrow \text{replace}(g, w, w') \)
32: \( \text{if } g_{im} \notin \mathcal{G}_d \text{ then} \)
33: \( \mathcal{G}_m = \mathcal{G}_m \cup \{g_{im}\} \)
34: \( \text{end if} \)
35: \( \text{end for} \)
36: \( \text{end if} \)
37: \( \text{end for} \)
38: \( \text{end for} \)
39: \( \text{end for} \)
Figure 10. Policy architecture (modular-attention)

Figure 11. Venn diagram of goal spaces.
| Goals from $G^{\text{train}}$ | $G^{\text{train}}$ Type 1, 3, 4 and 5, see Table 1 |
|--------------------------------|--------------------------------------------------|
| Goals from $G^{\text{test}}$ | Semantically meaningless goals                    |
| Go bottom top, Go left right | Go center bottom, Go center top                  |
| Grasp red blue thing, Grow blue red thing | Go right center, Go right bottom                  |
| Go right left, Go top bottom | Go right top, Go left center                      |
| Grasp green blue thing, Grow green red thing | Go left bottom, Go left top                       |
| Grasp green red thing, Grasp blue green thing | Grow green cupboard, Grow green sink              |
| Grasp blue red thing, Grasp red green thing | Grow blue lamp, Go center right                   |
| Grow blue red thing, Grow red green thing | Grow green window, Grow blue carpet               |
| Grow red supply, Grow any sofa | Grow red sink, Grow any chair                     |
| Grow red sink, Grow any chair | Go top center, Grow blue table                    |
| Grow any door, Grow any lamp | Grow left bottom, Go left top                     |
| Grow blue sink, Go bottom center | Grow blue door, Grow blue supply                  |
| Grow blue door, Grow blue supply | Grow green carpet, Grow blue furniture            |
| Grow green carpet, Grow blue furniture | Grow green supply, Grow any window               |
| Grow any carpet, Grow green furniture | Grow any carpet, Grow green food                  |
| Grow green chair, Grow green food | Grow any cupboard, Grow red food                 |
| Grow any table, Grow red lamp | Grow red door, Grow any food                      |
| Grow red window, Grow red sofa | Grow blue window, Grow red desk                   |
| Grow blue sofa, Grow blue desk | Grow any sink, Grow red cupboard                 |
| Grow any sink, Grow red cupboard | Grow green door, Grow red furniture              |
| Grow green door, Grow red furniture | Grow blue food, Grow red desk                     |
| Grow blue food, Grow red desk | Grow red table, Grow blue chair                   |
| Grow red sofa, Grow any furniture | Grow red window, Grow any desk                   |
| Grow red window, Grow any desk | Grow blue cupboard, Grow red chair               |
| Grow blue cupboard, Grow red chair | Grow green desk, Grow green table                |
| Grow green desk, Grow green table | Grow red carpet, Go center left                   |
| Grow any supply, Grow green lamp | Grow any supply, Grow green lamp                  |
| Grow blue water, Grow red water | Grow blue water, Grow red water                   |
| Grow any water, Grow green water | Grow any water, Grow green water                  |

Table 2. All imaginable goals $G^{im}$
7. Supplementary Results

7.1. Supervised Learning of the Reward Function

We provide the evolution of the $F_1$-scores on $G^{\text{train}}$ and $G^{\text{test}}$ for the three architectures presented (Fig 12). The final points at Epoch=300 are the one presented in Main Fig. 3a. The MA architecture significantly outperforms its competitors, both in terms of $F_1$-score performances and sample efficiency. Only 150 epochs are required to achieve convergence while the competing architectures FC and FA barely converge after 300 epochs.

![Figure 12. Reward function convergence.](image)

Figure 12. Reward function convergence. Evolution of the $F_1$-score of the reward function on $G^{\text{train}}$ (plain) and on $G^{\text{test}}$ (dashed) during 300 epochs of training for various architectures.

7.2. Reward function zero-shot generalization

When the reward function is co-trained with the policy, we monitor its zero-shot generalization capabilities by computing the $F_1$-score over $G^{\text{test}}$ using the dataset collected in Section 6.2.1. Results are shown in Fig. 13. The reward function exhibits good generalization properties over 4 types of generalization after $25 \times 10^3$ episodes. Note that the $F_1$-scores presented in Fig 13 may not faithfully describe the true generalization of the reward function during co-training. Indeed, the testing performance of the reward function is computed over a dataset of trajectories collected from a different RL policy (kept fix for all runs).

![Figure 13. Evolution of the $F_1$-score of the reward function on $G^{\text{train}}$ and the different types of goals from $G^{\text{test}}$ during policy training](image)

Figure 13. Evolution of the $F_1$-score of the reward function on $G^{\text{train}}$ and the different types of goals from $G^{\text{test}}$ during policy training.

7.3. Visualizing Goal Embedding

To analyze the goal embeddings learned by the language model $LM$, we perform a t-SNE using 2 components, perplexity 20, a learning rate of 10 for 5000 iterations. Figure 14 presents the resulting projection for a particular run. The embedding seems to be organized mainly in terms of motor predicates (14a), then in terms of colors (14b). Object types or categories do not seem to be strongly represented (14c).

![Figure 14.](image)

Figure 14. t-SNE projection of goal embeddings.

7.4. Visualizing Attention Vectors

In the modular-attention architectures for the reward function and policy, we train attention vectors to be combined with object-specific features using a gated attention mechanism. In each architecture, the attention vector is shared across objects (permutation invariance). Figure 15 presents examples of attention vectors for the reward function (15a) and for the policy (15b) at the end of training. These attention vectors highlight relevant parts of the object-specific sub-state depending on the NL goal:

- When the sentence refers to a particular object type (e.g. dog) or category (e.g. living thing), the attention vector suppresses the corresponding object type(s) and highlights the complement set of object types. If the object is of the wrong type, the output of the Hadamard product between object types and attention will be non-zero. Conversely, if the object is of the required type, the attention suppression ensures that the output stays close to zero.

- When the sentence refers to a navigation goal (e.g. go top, the attention highlights the agent’s position (here $y$).

- When the sentence is a grow goal, the reward function focuses on the difference in object’s size, while the policy further highlights the object’s position.

The attention vectors use information about the goal to highlight or suppress parts of the input using different strategies depending of the type of input (object categories, agent’s position, difference in size etc). This type of gated-attention improves the interpretability of the reward function and policy.
7.5. Exploration Metrics

Here, we present additional exploration metrics to study the influence of goal imagination on exploration. In addition to exploration metrics on the training and testing sets of goals, we introduce a set of interesting interactions called extra set. This set contains interactions where the agent brings water or food to a piece of furniture or a plant. Although bringing supplies to a piece of furniture or food to a plant does not achieve any of the goals, we consider them as interesting exploratory behaviors, as it testifies that the agent tries to achieve its own imagined goals. We present two types of exploration metrics:

- In the first type, we count the number of interesting interactions computed over all final transitions from the last 600 episodes. Computed on the training set, it is the number of times any goal of the training set was reached at the end of an episode. We call this metric Interesting Interaction Count or $I^2C$. Computed on the training set, this gives:

$$I^2C_{\text{train}} = \sum_{i \in \mathcal{I} \in \mathcal{G}_{\text{train}}} \sum_{t=1}^{600} \delta_{i,t}$$

where $\delta_{i,t} = 1$ if interaction $i$ was achieved in episode $t$, 0 otherwise and $\mathcal{I}$ is the set of interesting interactions performed during an epoch (here training goals). Goal-imaging agents experience more interactions from the testing set and way more interactions from the extra set when compared to agents prohibited from imagining goals, see Fig. 16a to 16c.

- The second type of exploration metrics takes into account rarity. Rare experience is more valuable than common experience, thus, we weight each new interaction (e.g., growing a red plant) by a rarity score that is the inverse of the corresponding interaction count since the start $1/c_i$. Measures are reported as the sum of (rarity-weighted) interaction counts over the last 600 episodes, we call this Rarity-Weighted $I^2C$ or $RW-I^2C$. When computed on the training set:

$$RW-I^2C_{\text{train}} = \sum_{i \in \mathcal{I} \in \mathcal{G}_{\text{train}}} \sum_{t=1}^{600} \frac{\delta_{i,t}}{c_i}$$

Agents allowed to imagine goals achieve higher scores in all sets of interactions, see Fig. 16d to 16f. We hypothesize that higher scores on the training set come from an indirect effect. Agents that imagine goals have a higher probability to sample grow goals than other agents as they represent a larger proportion of goals available to them. Since scenes are created to make target goals achievable, this leads to an increase in the probability of supplies being sampled (required to achieve grow goals). When supplies are present more often, it increases the probability to grow animals (rarest goals in the training set), which in turn increases the training exploration score.

7.6. Confusing Scenes

When evaluating our agent offline on the set of training goals, it might be that our agent manages to achieve the goal grasp red tree, by understanding only the word red or only the word tree. As the scene only contains 3 objects, the probability to have only one red object or only one tree is high. To make sure our agent does understand all terms in the goal, we tested it in confusing settings. For instance, a scene to test grasp red tree could contain a red tree, a red cat and a green tree. Comparing evaluation results for confusing scenes versus normal scenes, we did not find any significant difference in performances: $\mu_{\text{confusing}} = 0.981$, $\mu_{\text{normal}} = 0.975$, p-value = 0.44 computed over 10 seeds.

7.7. Computing Resources

The RL experiments contain 12 conditions of 10 seeds each. Each run leverages 6 cpus (6 actors) for about 36h for a total of 2.9 cpu years.

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Figure 14. t-SNE of goal embedding. The same t-SNE is presented, with different color codes: a: predicates, b: colors, c: object categories.
Figure 15. Attention vectors a: $\alpha$ for the reward function (1 seed). b: $\beta$ for the policy (1 seed)
Figure 16. Exploration metrics a: Interesting interaction count ($I^2C$) on training set, b: $I^2C$ on testing set, c: $I^2C$ on extra set. d: Rarity-weighted $I^2C$ on training set, e: Rarity-weighted $I^2C$ on testing set, f: Rarity-weighted $I^2C$ on extra set.