An Emergent Symbolic Representation of Space as a Bridge Between Language and Reinforcement Learning in Continuous Environments

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Abstract

Large Language Models (LLMs) exhibit their potential for interacting with reinforcement learning (RL) agents, for instance as high-level planners. However, space representation still impedes their application for embodied agents. We tackle this problem by taking advantage of a discrete world representation learned online by reinforcement learning. Our proposed algorithm, SGIM-STAR is a hierarchical RL method where the top-level agent is augmented with a partition-wise, learning-progress–driven switch between a RL-based planner and an LLM planner. The agent builds a discrete reachability-based partition of space online and uses intrinsic motivation to query the LLM only when beneficial, defaulting to RL as planner otherwise. This yields usage/cost efficiency: the RL-based planner dominates early and the LLM is leveraged as the representation matures. In Ant Maze, SGIM-STAR achieves the best and most stable success among STAR, LLM-only, and a non-partitioned adaptive variant, avoiding mid-training collapses while reducing LLM calls. The results demonstrate a practical fusion of LLMs taking advantage of emerging symbolic models of the environment for long-horizon tasks.

1 Introduction

Recent foundation models have shown that Large Language Models (LLMs), although trained mostly on abstract content such as from web scrapping, can carry internal world models [Shentu et al., 2024, Chakraborty et al., 2023, Jang et al., 2024, Driess et al., 2023, Ma et al., 2023, Zitkovich et al., 2023] that can be exploited for effective interaction in embodied AI to drive reinforcement learning and planning agents [Hu et al., 2019, Carta et al., 2025]. However, their performance is poor in the case of real-world inference because of the grounding problem [Jokinen, 2024]. Although training the LLMs on massive text data can endow LLMs with a representation of the world, the connection to sensory modalities of the real world is essential to solve a wider range of problems grounded in the physical world such as in robotics. Moreover, the shortcomings of LLMs hardly predictable, especially for open-ended worlds. Thus, the world models of LLMs need to be probed to identify their limitations and capabilities, so as to enhance them. In this work, we use the intrinsic motivation [Gottlieb et al., 2013, Schmidhuber, 1991] empirical measure of learning progress to assess their limitations and capabilities.

Another limitation of the use of LLMs for effective interaction within dynamic environments is the opposition of a symbolic representation of the world by LLMs and the continuous world of physical embodied environments. We need to bridge this gap by learning a symbolic representation of the environment that aligns with the LLM symbols. Thus, we propose an algorithm that creates online a discrete world representation by reinforcement learning exploration and combines it with

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symbols from an LLM. As open-learning tasks, we will address long-horizon tasks with a hierarchical reinforcement learning (HRL) algorithm enhanced by an LLM. To address long-horizon tasks by building discrete representations, HRL algorithms using reachability analysis have successfully solved problems as in Ant Maze environments [Zadem et al., 2023, 2024]. To further these works by taking advantage of the internal world representation of LLMs, the top-level agent of our algorithm can identify its limitation and actively choose between an LLM-driver planner and a Q-learning planner, using intrinsic motivation criteria. This combination can enhance the world representation of our system. As such, our algorithm combines an emerging symbolic representation using a partition of space output by a bottom-up process based on reinforcement learning, and symbols from an LLM as a planner to top-down exploration of the embodied environment.

2 Related Works

2.1 Space Representation for Hierarchical Reinforcement Learning

To address complex tasks which involve long-term planning and multi-step actions, HRL algorithms decompose a task into simpler subtasks, allowing them to be subsequently solved efficiently. HIRO [Nachum et al., 2018] introduced a two-level manager–controller for continuous control with off-policy data by exploiting temporal abstraction; HAC [Levy et al., 2019] complexified the architecture into multiple levels of reinforcement learning agents to address longer-horizon tasks. HRAC [Zhang et al., 2020] approximates reachability to propose subgoals in k-step adjacent regions, but computing reachability relationships in continuous high-dimensional spaces is costly.

While HAC and HIRO sample subgoals from the raw state space, recent HRL algorithms sought to solve the curse of dimensionality problem of subgoal space by learning a representation of the subgoal space. LESSON learns latent slow features to capture long-horizon dynamics [Li et al., 2021]. GARA [Zadem et al., 2023] and STAR [Zadem et al., 2024] solved the computational cost problem of HRAC by discretizing the subgoal space : they partition the state space to build reachability-aware regions and refine them based on learned k-step reachability, combining spatial abstraction with hierarchical control. While GARA used a two-level agent, STAR uses a 3-level agent to address higher-dimensional environments, showing good results in 5-D continuous state spaces, but these results can be unstable. To address long-horizon tasks in robotic real-world environments that are high-dimensional, we extend this line of work to enhance this space abstraction with complementary mechanisms to stabilize the performance.

2.2 Socially Guided Intrinsic Motivation

To address sparse-reward multi-task learning, Intrinsic Motivation (IM) [Gottlieb et al., 2013, Schmidhuber, 1991] drives the exploration by automatic curriculum learning before obtaining any non-zero external reward. Intrinsic motivation has used several measures for active learning [Oudeyer and Kaplan, 2007], such as novelty, competence Oudeyer et al. [2005] or progress [Baranes and Oudeyer, 2013]. However, IM still meets limitations in high-dimensional task spaces. To complement reinforcement learning, human-in-the-loop approaches Retzlaff et al. [2024] such as reinforcement learning from human feedback Knox et al. [2013] have been developed. Imitation learning [**?**] and inverse-RL methods [Finn et al., 2016, Fu et al., 2018] serve as computational frameworks for social guidance in robotics, by either transposing a policy from demonstrations or learning a reward signal.

Whereas most human-in-the-loop algorithms have considered the learning agent as passive in their interaction with humans, *active imitation learning* proposes algorithms for the learning agent to actively request information from teachers Shon et al. [2007], with for instance the sucessful algorithm DAGGER Ross et al. [2011]. For robots, *Socially Guided Intrinsic Motivation (SGIM)* couples IM with social guidance to enable the agent to actively decide on different aspects of its interaction with the teachers : while teachers are available to provide demonstrations of policies, goals [Nguyen and Oudeyer, 2012b], or task decomposition [Duminy et al., 2021], while the agent chooses what, when, how and whom to imitate based on learning progress [Nguyen and Oudeyer, 2012b]. This yields an adaptive curriculum that focuses its requests for demonstrations where competence improves fastest, enabling efficient exploration in high-dimensional spaces, by benefiting from implicit world models from teachers. Our work adopts the same mechanism of active choice between reinforcement learning or requesting expert help based on intrinsic motivation.

2.3 Large Language Models in Decision-Making

Recent breakthroughs in LLMs have significantly expanded their capabilities beyond natural language processing to complex reasoning and decision-making tasks. Studies have explored using LLMs as planners or controllers in robotic systems, highlighting their potential to exploit internal world representations within LLMS. Hu et al. [2019] generates a plan in natural language, which is then executed by a separate model.

However, integrating LLMs into reinforcement learning frameworks remains challenging due to poor space representation of a continuous environment, whereas LLMs use a discrete, symbolic representation. Jiang et al. [2019] uses language as the interface between high- and low-level policies in hierarchical RL, with a low-level policy that follows language instructions, and the top-level policy producing actions in the space of language. In Shentu et al. [2024], LCB uses a learnable latent code to act as a bridge between LLMs and low-level policies. This enables LLMs to flexibly communicate goals in the task plan without being entirely constrained by language limitations. To alleviate the lack of grounding of LLMs in space, these works add to the reinforcement learning agents a new layer to translate between the continuous space of states and the discrete space of LLM symbols. However, the reinforcement learning algorithms GARA and STAR learn directly a discrete representation, which symbols can be more readily used by a LLM. In this work, we explore how the emerging symbolic representation of STAR can be exploited by LLMs.

Our *contribution* is to study how a symbolic representation of space can be taken advantage of by LLMs for learning long-horizon tasks. Our proposed algorithm, SGIM-STAR, in the HRL framework with a high-level agent can actively choose its learning strategy between reinforcement learning or a LLM-based planner. The originality is that both strategies use a symbolic representation of the sensorimotor space, by learning an emergent symbolic representation, making it compatible with the symbolic space of language.

We first explore whether a space partition into regions learned online by HRL can have a correspondence with natural language instructions in section 3. To exploit this correspondence, we introduce in section 4 the algorithm SGIM-STAR, which chooses between a LLM-based planner or a RL-based planner based on intrinsic motivation. The experimental results are presented in section 5, where we test SGIM-STAR in Ant Maze environment, originally introduced by Duan et al. [2016] and later popularized in hierarchical reinforcement learning benchmarks by Nachum et al. [2018].

3 Spatial Abstractions used to Translate Natural Language Instructions

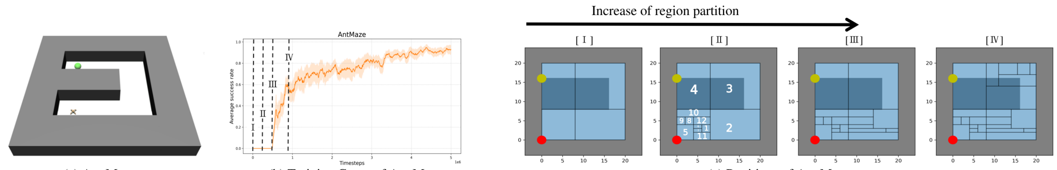
We examine how symbolic spatial abstractions can be used for grounding language. In this section, we outline the algorithm STAR, then report our first investigation whether language can be grounded in the emergent spatial abstraction.

3.1 Preliminary: Spatio-Temporal Abstraction via Reachability (STAR)

The STAR algorithm Zadem et al. [2024] is a reinforcement learning algorithm that uses a three-layered hierarchical structure:

- Navigator: the top-level agent plans the long-horizon path. It is trained by Q-learning which samples an abstract goal $G \in \mathcal{G}$ every k steps that should help to reach the task goal g^* from the current agent's state $(G_{t+k} \sim \pi_{Nav}(s_t, g^*))$.
- Manager: the mid-level agent trained by TD3 which picks subgoals in the state space every l steps $(g_{t+l} \sim \pi_{Man}(s_t, G_{t+k}))$, we notice that k is a multiple of l.
- Controller: the low-level policy trained by TD3 that samples actions to reach the subgoal every step $(a \sim \pi_{Cont}(s_t, g_{t+l}))$

STAR incrementally refines the partition of the sensorimotor space (cf. Fig. 1 (c)) by analyzing k-step reachability relations between goal regions. The Refinement module uses as inputs the past episodes $\mathcal{D}$ and a the list of abstract goals $\mathcal{E}$ visited during the last episode, and outputs a partition of the state space.



(a) Ant Maze (b) Training Curve of Ant Maze (c) Partitions of Ant Maze

Figure 1: (a) Ant Maze environment, (b) Average success rate of STAR (from Zadem [2024]), (c) Partition into regions of STAR. The regions in (c) are the internal representation emerging during the training at timestamps noted in (b). The red point is the initial position of the robot. The yellow point is the goal position. Our translator translates instructions to guide the robot (eg: "go east to the end, turn north until past the wall and go west until the end"), into a sequence of traversed regions (eg for Partition II, the output is $5 \rightarrow 11 \rightarrow 2 \rightarrow 3 \rightarrow 4$).

Table 1: Mean G-BLEU scores of translation of natural language instructions over 4 runs for each partition in the Ant Maze environment.

translator	**Ant Maze**			
	P-I	P-II	P-III	P-IV
GPT o3-m	1	1	1	0.87
Claude	1	1	0.73	0.34
Deepseek	1	0.9	0.53	0.65
GROK	1	1	1	0.89

3.2 Translation of Natural Language to the Spatial Abstraction

In the first experiment, we probe the possibility of grounding instructions in natural language by means of a spatial abstraction leaned from a reinforcement learning. Concretely, we test if we can translate the plan outlined by natural language instructions into a succession of subgoals. For this translation, we exploit and evaluate several LLMs in interpreting fixed natural language instructions across varying symbolic abstractions. We keep the agent's start and goal positions fixed and apply the same instruction to all partition levels. The natural language instruction for Ant Maze is: "Move right until you completely pass the wall on your left, move up until you have crossed the upper wall, turn left and proceed until you reach the goal."

We report in Table 1 the G-BLEU score for the translation of this instruction into a sequence of regions by four commonly used reasoning LLMs: GPT o3-mini, Claude 3.7, DeepSeek-r1, and GROK. While GPT o3-mini achieves the highest scores, all translators achieve scores above 0.5 across tasks, indicating a generally successful translation of human instructions into the agent's internal symbolic representation. In the Ant Maze environment, all translator scores decrease as the number of regions increases. However, the degradation of performance varies by model: GPT o3-mini and GROK demonstrate greater robustness than DeepSeek-r1 and Claude 3.7.

Given the consistent trends observed across LLMs, we select GPT o3-mini as the representative LLM for subsequent experiments.

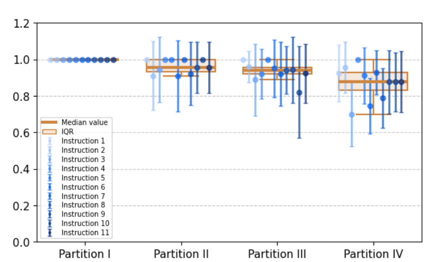


Figure 2: G-BLEU scores for translation of natural language instructions tested in Ant Maze. For each internal representation, we plot in blue the average and standard deviation of 10 queries for each instruction, and boxplot in brown, orange and yellow the average and IQR over the 11 instructions.

In order to test the robustness of the previous results with statistical tests, for our second experiments, we design 11 different natural language instructions for each environment (cf. Appendix B), and tested all 11 instructions on all four partitions. We constructed the prompt (cf. Appendix C and queried the LLM 10 times. Figure 2 illustrates the average G-BLEU scores across the symbolic partitions of Ant Maze. We observe a perfect translation performance in Partition I. The trend of translation performance observed in Ant Maze is a consistent slightly drop from Partition I to Partition IV. This trend is interpretable through the partition structures shown in Figure 1. Partition I represents a very coarse abstraction with minimal region division, making it easier for the LLM to infer plausible region sequences regardless of the instruction quality. Then, when the partition becomes more granular in Ant Maze, the LLM is more prone to mistakes.

4 SGIM-STAR : Combining LLM and RL as planners

Our proposed algorithm follows STAR's hierarchical structure and reachability-aware abstraction, but augments the high-level agent with a large language model (LLM) and introduces a partition-wise, progress-driven *active choice* between a (Q-learning) RL-based planner and an LLM planner. This design aims to keep low-level learning intact while (i) leveraging language for top-level guidance when beneficial, (ii) reducing LLM usage cost by invoking it only when progress warrants it, and (iii) improving stability on long-horizon tasks via per-partition selection rather than a single, global switch. In this section, we outline STAR, our integration of an LLM at the high level and the active imitation mechanism.

4.1 Integration of an LLM into the Top Level Agent

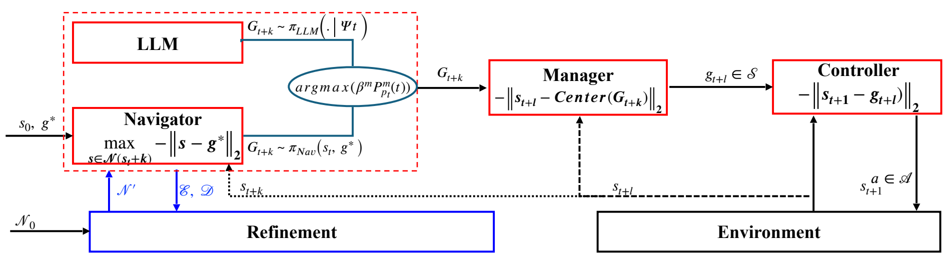


Figure 3: Algorithmic architecture of SGIM-STAR which integrates the LLM and the Navigator of STAR at the top level agent. The Navigator or the LLM selects subgoal regions $G \in \mathcal{G}$, while the middle-level manager and low-level controller are unchanged. The choice between the LLM and the Navigator.

We extend STAR by incorporating an LLM into the top-level agent. The structure is shown in Fig. 3. Instead of relying solely on the Navigator policy $\pi_{\text{STAR}}(G|s_t)$, we introduce an LLM-based planner $\pi_{\text{LLM}}(G|\Psi_t)$, which operates on a prompt Ψ_t encoding the agent's current region, available partitions, and task description. Thus, the top-level goal selection becomes:

$$G'_{t+k} \sim \pi_{\text{LLM}}(\cdot \mid \Psi_t), \quad \Psi_t = \psi(s_t, \mathcal{G}_N, g^*, \mathcal{M}_t), \tag{1}$$

where $\mathcal{G}_N$ is the set of admissible regions, g^* is the task goal, and $\mathcal{M}_t$ summarizes recent exploration. This modification allows the Navigator to integrate human-readable instructions and world knowledge expressed in natural language, thereby aligning regional exploration with external guidance or commonsense priors.

4.2 Active Imitation Learning of the Top Level Agent

To dynamically balance between the original STAR Navigator and the LLM-based planner, we use intrinsic motivation based on progress measure as a selection mechanism.

Initialization. For the first N decision steps, the planner is chosen randomly between the Navigator and LLM in order to populate both buffers with initial experience.

Progress signal. At each timestep t, let $m \in \{\text{STAR}, \text{LLM}\}$ denote the planner used, and let $p_t = \phi(s_t)$ be the current region of the state space. We define the incremental reward difference: $\Delta_t = r_t - r_{t-1}$ which reflects the immediate progress attributable to the planner's decision at t. This value Δ_t is stored as $\Delta_t^{(m)}$ in the buffer of the corresponding planner m for the active region p_t.

Discounted progress accumulation. For each region p_t and planner m, we compute a discounted cumulative progress over a sliding window of length n:

$$P_{p_t}^{(m)}(t) = \sum_{j=0}^{n} \alpha^j \, \Delta_{t-j}^{(m)} \tag{2}$$

where $\alpha \in (0, 1)$ is a progress discount factor that emphasizes recent progress while retaining memory of past improvements.

Planner selection rule. At each decision step, the algorithm selects the planner according to a progress-maximization criterion:

$$m(t) = \underset{m \in \{\text{STAR}, \text{LLM}\}}{\arg\max} \left\{ \beta^{(m)} P_{p_t}^{(m)}(t) \right\}, \tag{3}$$

where $\beta^{(\text{LLM})} \geq 0$ is a scaling factor that controls the relative influence of LLM-derived progress ($\beta^{(\text{STAR})} = 1$).

Algorithm 1 SGIM-STAR

Require: Discount factor $\alpha \in (0, 1)$, window size $n \in \mathbb{N}$, warm-start steps $N \in \mathbb{N}$,
    Weights $\beta^{(\text{LLM})} \geq 0,\ \beta^{(\text{STAR})} = 1$
    Planners $\mathcal{M} = \{\text{STAR}, \text{LLM}\}$; partition map $\mathcal{P}_0 = \phi(s_0)$
Initialize
    $\forall$ region $p \in \mathcal{P}_0, \forall$ planner $m \in \mathcal{M}$, initialise buffer $\mathcal{B}_p^{(m)}$ at capacity $n{+}1$ to store Δ values
    $\forall$ region $p \in \mathcal{P}_0, \forall$ planner $m \in \mathcal{M}$, discounted progress scores $P_p^{(m)} \leftarrow 0$
    $t \leftarrow 0$, observe s_0 and reward r_0
while episode not terminated **do**
    $p_t \leftarrow \phi(s_t)$ {Identify current region}
    if $t < N$ **then**
        Choose $m(t) \sim \text{Uniform}(\mathcal{M})$ {Warm-start randomization}
    else
        Compute weighted scores in region p_t:
        $P_{p_t}^{(m)}(t) = \sum_{j=0}^{n} \alpha^j \, \Delta_{t-j}^{(m)}$
        $m(t) \leftarrow \underset{m \in \{\text{STAR}, \text{LLM}\}}{\arg\max} \left\{ \beta^{(m)} P_{p_t}^{(m)}(t) \right\}$
    end if
    Use planner $m(t)$ to select top-level region G_t and act for one decision step
    Observe next state s_{t+1} and reward r_{t+1}
    $\Delta_{t+1}^{(m(t))} \leftarrow r_{t+1} - r_t$ {Incremental reward difference}
    Append $\Delta_{t+1}^{(m(t))}$ to buffer $\mathcal{B}_{p_t}^{(m(t))}$ (drop oldest if $|\mathcal{B}_{p_t}^{(m(t))}| > n{+}1$)
    $t \leftarrow t + 1$, $r_t \leftarrow r_{t+1}$, $s_t \leftarrow s_{t+1}$
end while=0

We notice that if a region p has already been well explored, then both planners yield low incremental progress ($\Delta_t^{(m)} \approx 0$), resulting in small accumulated scores $P_p^{(m)}(t)$. Conversely, when the agent enters a novel region, progress signals tend to be larger, biasing selection toward the planner that has demonstrated stronger improvement in unexplored regions. This mechanism naturally encourages exploitation of novel areas while reducing reliance on planners that fail to generate additional progress in familiar regions.

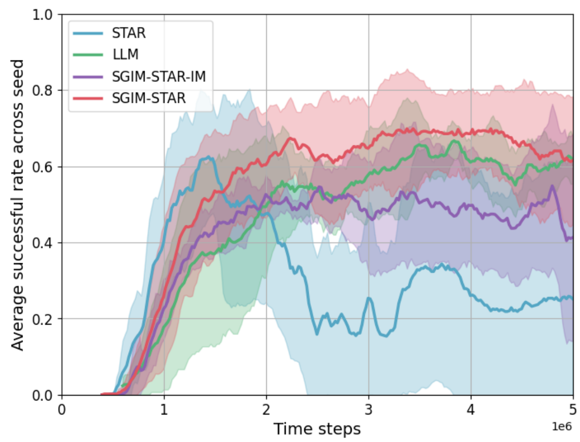


Figure 4: Average successful rate of four methods

5 Performance of SGIM-STAR

5.1 Experiment Setup

We evaluate our proposed algorithm, SGIM-STAR in the Ant Maze environment. Our primary evaluation task is Ant Maze, in which the Ant robot must navigate a $\supset$-shaped maze and reach an exit located at the top left corner. This task is inherently hierarchical: success requires both fine-grained locomotion control (low-level) and long-horizon navigation through the maze (top-level). Moreover, Ant Maze is a suitable benchmark for evaluating LLM integration, as solving the task requires reasoning over abstract spatial regions and selecting long-horizon subgoals rather than relying solely on local control.

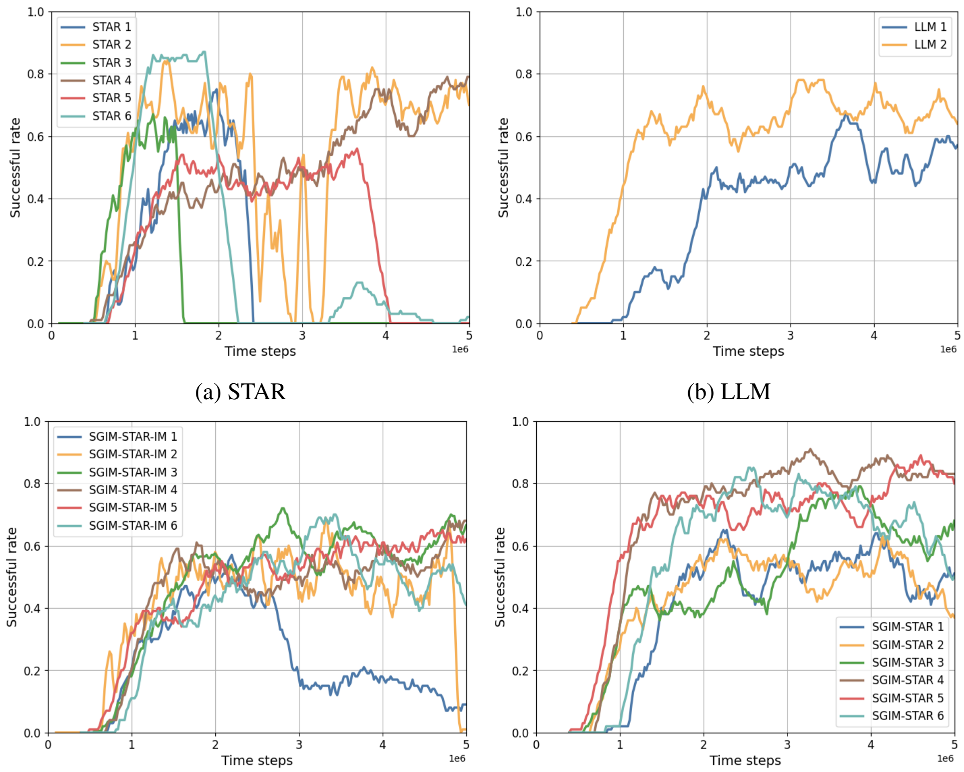
The prompt design used for the LLM-based planner in Ant Maze is provided in the Appendix. We compare our SGIM-STAR with the following methods:

- **STAR**: the original STAR framework where the high-level agent is the Navigator policy trained via Q-learning.
- **LLM Planner**: STAR algorithm where the Navigator is replaced by an LLM using a handcrafted prompt. The Manager and Controller remain unchanged.
- **SGIM-STAR-IM** (SGIM-STAR with Interactive learning at the Meta level) : to study the importance of the partition, we considered an ablation where the top-level agent adaptively switches between STAR and LLM, but without considering the environment partitions defined by the STAR abstraction, as with the algorithm SGIM-IM Nguyen and Oudeyer [2012a]: instead of computing $\mathcal{P}_{pt}^{(m)}$ for each region, we consider it for the whole state space.

All agents are trained to navigate the maze to a goal location, and we track their success rates over 5 million environment step on 6 random seeds for SGIM-STAR, SGIM-STAR-IM and STAR, and 2 seeds for LLM Planner, all experiments are trained on one NVIDIA GEFORCE RTX 4090 GPU.

5.2 Results and Analyses

Fig.4 shows the average success rate across random seeds for each approach. We observe that the partition-based method not only attains the greatest success rate of 0.7 by the end of training but also exhibits the smallest variance across seeds, indicating consistent learning outcomes. In contrast, the other methods reach lower success levels and have wider fluctuations. Notably, the LLM-only agent plateaus around a moderate success rate at around 0.6, while the pure STAR agent's average performance degrades significantly by the end of training due to collapses in some runs (Fig.5a). These results demonstrate that incorporating partitioned task structure and adaptively integrating LLM guidance produces superior resilience in this long-horizon task.

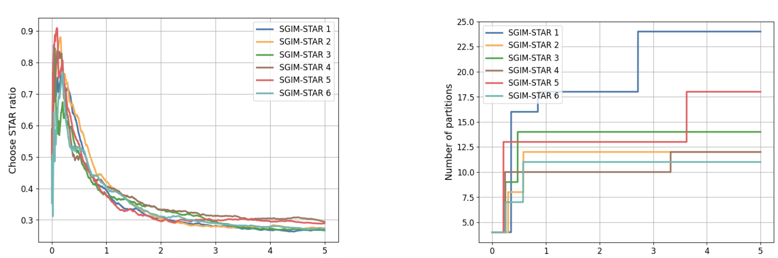


(a) STAR (b) LLM

(c) SGIM-STAR-IM (d) SGIM-STAR

Figure 5: Successful rate of each run

To further analyze stability, we examine individual training curves of each method. The pure RL baseline STAR, as shown in Fig.5a, collapses frequently mid-training across seeds. This instability indicates a lack of resilience: the convergence of STAR is not guaranteed when learning such a complex, long-horizon task without additional guidance. Figure 5b shows that the LLM-only agent can reach moderate success rates plateau without any dropping of performance, demonstrating the potential of a pretrained planner to guide exploration. However, the use of LLM-planner is too costly and the learning process of LLM-only is three times slower than the others, which limits the further use of LLM in the top-level agent. Fig.5d shows that SGIM-STAR demonstrates remarkably consistent improvement across training, with almost no catastrophic drops in performance. In contrast, the SGIM-STAR-IM variant also suffers abrupt performance collapses after initial learning spurts from Fig,5c. This suggests that state-space partitioning plays a critical role in stabilizing long-horizon learning.



(a) The ratio of chosen STAR (b) Environment Partitions

Figure 6: Adaptive choice of Planner by Partition

A key insight is that SGIM-STAR selectively shifts to LLM guidance once it becomes beneficial. Early on, STAR's fast learning of basic navigation yields quicker gains, so the agent heavily favors the STAR Navigator policy. As training progresses, the agent discovers a more refined symbolic structure of the maze via partitions, it increasingly relies on the LLM for top-level planning. Fig.6a quantifies this behavior: at the start of training, the fraction of top-level choices directed by STAR is extremely high, as the task structure emerges, this fraction steadily declines, and by the end of training the agent chooses STAR for only one third of decisions on average, indicating that it has shifted to predominantly following the LLM's guidance in later stages. In other words, SGIM-STAR intelligently "trusts" STAR in the beginning when the LLM's abstract guidance might not yet be enough, and then gradually transitions to the LLM as the partitions learned by STAR provide a reliable framework for planning. This adaptive scheduling of who controls the top-level actions is crucial to achieving both high efficiency and stability.

Another contributing factor to the robustness of the SGIM-STAR is the growth of its state abstraction over time. During training, the SGIM-STAR incrementally partitions the state space into more regions as it encounters new situations. Fig.6b tracks the number of partitions in each run over the course of training. In effect, the partitioning mechanism provides a form of symbolic memory that the LLM can leverage which grounds the LLM's planning in the agent's learned experience.

6 Discussion

After showing a possible parallel between natural language instructions and spatial abstraction, which hints a grounding of LLMs in a space representation, we introduced SGIM-STAR which selectively combines a RL-based planner with an LLM-based planner using a partition-wise, progress-driven rule. Our analysis yields four key characteristics of our method:

(1) Mutual stabilization and lighter planning. LLM guidance stabilizes STAR by providing supplementary top-level proposals when the RL-based planner becomes brittle, while STAR makes the overall system lighter than an LLM-only planner by supplying competent, inexpensive planning during large portions of training. Overall, the RL-based planner constitutes a bottom-up agent learning from its trial and error with the environment, whereas the LLM planner is a top-down agent sharing its internal world representation to this specific task. Their combination mutualizes both a bottom-up and a top-down process. The instrinsically motivated, progress-based selection between the two planners improves learning progress and stabilizes performance.

(2) Cost-aware usage of the LLM. SGIM-STAR uses the LLM only when necessary: calls to the LLM are conditional on partition-wise progress and thus avoided when the STAR navigator suffices. Compared to an LLM-only navigator, this conditional usage reduces planner cost and latency while still reaping the benefits of LLM exploration.

(3) Start planning with RL, then switch to LLM. The agent relies more on a RL planner in the early phase—when the internal representation is coarse—and gradually shifts toward LLM guidance as the internal representation becomes richer and more meaningful for language reasoning.

(4) Formulation that enables language grounding. Crucially, our learning formulation builds a discretized, partitioned representation—from bottom-up RL experiences. This evolving symbolic structure leverages LLMs to help the learning process of the agent, by offering a grounded correspondence of regions to LLM symbols.

7 Conclusion

We present *SGIM-STAR*, a simple, partition-wise-progress-based algorithm that switches between a STAR high-level planner and an LLM planner. In Ant Maze, it achieves the best and most stable results, avoiding STAR's mid-training drops and the high cost and low efficiency of an LLM-only planner. The LLM stabilizes STAR when learning becomes unstable, while STAR keeps the system light by handling most decisions—so we use the LLM only when needed. As the state-space partition grows during training, the agent uses STAR more frequently at the early stages of training while soliciting the LLM more in the later ones, since the richer representation gives the LLM more meaningful inputs. This indicates that a richer internal representation can offer a better spatial grounding of LLM planners. This combination makes training steadier and more efficient than using STAR or an LLM alone, owing to SGIM's active choice. SGIM-STAR thus autonomously devises learning curriculum and strategy, starting with a RL planner then switching to LLM planner.

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Appendix

A Prompt

```
Data:
-State: Region 5
-Goal: Region 4

-Adjacency list:
    Region 1: [6, 7, 11, 12, 14, 18]
    Region 2: [12, 13, 14, 15]
    Region 3: [4, 19, 21]
    Region 4: [3]
    Region 5: [6, 7, 8, 9, 11]
    Region 6: [1, 5, 7, 11]
    Region 7: [1, 5, 6, 12]
    Region 8: [5, 9, 10, 12]
    Region 9: [5, 8, 10]
    Region 10: [8, 9, 12, 13]
    Region 11: [1, 5, 6, 17]
    Region 12: [1, 2, 7, 8, 10]
    Region 13: [2, 10, 15]
    Region 14: [1, 2, 15, 18]
    Region 15: [2, 13, 14, 16, 18, 20]
    Region 16: [15, 17, 18]
    Region 17: [11, 16, 18]
    Region 18: [1, 14, 15, 16, 17]
    Region 19: [3, 20, 21, 22, 23]
    Region 20: [15, 19]
    Region 21: [3, 19, 22]
    Region 22: [19, 21, 23]
    Region 23: [19, 22]

-The top-down view of the maze is shown
 below, 'W' represents walls, 'A'
 represents the ant's current position,
 'G' represents the goal. The number
 represents the region number:

4  4  4  4  4  3  21 21 22 22 22 22 23
4  4  4  4  4  3  19 19 19 19 19 19 19
4  G  4  4  4  3  19 19 19 19 19 19 19
W  W  W  W  W  W  W  W  W  19 19 19 19
W  W  W  W  W  W  W  W  W  19 19 19 19
W  W  W  W  W  W  W  W  W  19 19 19 19
W  W  W  W  W  W  W  W  W  20 20 20 20
10 10 10 10 10 13 13 15 15 15 15 15 15
9  9  8  12 12 2  2  15 15 15 15 15 15
5  5  5  7  1  14 14 15 15 15 15 15 15
5  A  5  6  1  18 18 18 18 18 16 16 16
5  5  5  11 11 17 17 17 17 17 17 17 17


-Thinking Process:
   1.Identify the agent's current region
     and the goal region.
   2.Identify where is the wall.
   3.Examine the adjacency list and the
     maze to see which regions connect to
     the current region.
   4.From these connected regions, choose
     the one that moves closest to the goal
     without hitting walls.
```

B 11 Instructions given to the partitions in the Ant Maze environemnt

C Evaluating the Translation of Natural Language into Symbolic Abstractions

Let $S = \{s_1, s_2, \ldots, s_N\}$ denote the set of internal symbolic representations identified during the developmental learning process of STAR. We design a collection of instructions $I = \{I_1, I_2, \ldots, I_N\}$ from J humans, where each element is a set of instructions $I_i = \{I_{i,1}, I_{i,2}, \ldots, I_{i,J}\}$. Each instruction $I_{i,j}$ corresponds to a unique natural language command describing the goal or behavior related to s_i by the human j. We define a prompt construction function $f_{\text{prompt}}(s_i, I_{i,j})$ that takes a symbolic representation s_i and an associated instruction $I_{i,j}$ to generate a textual prompt $p_{i,j}$ for the LLM:

$$p_{i,j} = f_{\text{prompt}}(s_i, I_{i,j}) \tag{4}$$

Due to the stochastic nature of LLMs, a given prompt $p_{i,j}$ may result in different outputs across multiple queries. We introduce a random state r_k (*e.g.*, random seed) and define the LLM-generated output at query time k as:

$$o_{i,j,k}^{LLM} = \text{LLM}(p_{i,j}, r_k) \tag{5}$$

To establish a reference for evaluation, domain experts provide human-annotated ground truth outputs $G_{i,j}$ for each symbolic-instruction pair $(s_i, I_{i,j})$, so for each $G_i \in G$, $G_i = \{G_{i1}, G_{i2}, ..., G_{iJ}\}$. It is

Table 2: Natural language instructions for the Ant Maze environemnt

Instructions	Ant Maze
1	Move east until you are past the wall, then go north beyond the upper barrier, turn west, and continue until you reach the goal.
2	Head right until there's no obstruction in your way, then move up until the path is clear, turn left, and proceed to your destination.
3	Travel right to get around the first wall, ascend straight up to clear the second, then shift left and move toward the goal.
4	Move horizontally to the right until you pass the boundary, then go straight up until no walls remain, turn left, and continue forward.
5	Proceed east to navigate around the wall, then ascend north until you are clear, turn west, and move straight to your target.
6	Walk right until you exit the confined space, then go up beyond the vertical wall, turn left, and follow the open path to the goal.
7	Move sideways to the right until the wall is behind you, then climb upwards until there's no barrier, turn left, and walk toward the goal.
8	Head eastward until you escape the enclosed area, ascend northward past the last obstruction, then turn west and reach your goal.
9	Travel right along the open path until no wall blocks your way, go straight up past the top structure, then turn left and proceed to your destination.
10	Move toward the right until you have an open vertical passage, then go up until the way is clear, turn left, and walk directly to your goal.
11	Navigate eastward beyond the boundary, then ascend straight up to clear the structure, turn left, and reach the goal without further obstacles.

Algorithm 2 Translation by LLM of Human Instructions into Emergent Symbolic Representations

Require: $S = \{s_1, s_2, \ldots, s_N\}$: symbolic representations from STAR,
$I = \{I_1, I_2, \ldots, I_N\}$: set of human instructions sets,
$G = \{G_1, G_2, \ldots, G_N\}$: set of ground truth output sets
Ensure: $M = \{M_{1,1}, M_{1,2}, \ldots, M_{N,J}\}$: evaluation scores
for $i = 1$ to N **do**
  for $j = 1$ to J **do**
    $p_{i,j} \leftarrow f_{\text{prompt}}(s_i, I_{i,j})$
    for $k = 1$ to K **do**
      $o^{\text{LLM}}_{i,j,k} \leftarrow \text{LLM}(p_{i,j}, r_k)$
      $m_{i,j,k} \leftarrow \max_{q=1\ldots Q} M\left(o^{\text{LLM}}_{i,j,k}, G_{i,j,q}\right)$
    end for
    $M_{i,j} \leftarrow \frac{1}{K}\sum_{k=1}^{K} m_{i,j,k}$
  end for
end for=0

possible that multiple reference outputs are compatible with the pair $(s_i, I_{i,j})$, in this case we consider a set of references $G_{ij} = \{G_{i,j,1}, \ldots, G_{i,j,Q}\}$ for each $G_{i,j} \in G_i$. The set of ground truth output sets is the collection of all these references: $G = \{G_1, G_2, \ldots G_N\}$. We then define an evaluation metric $M\left(o^{\text{LLM}}, G\right)$ that measures the similarity between the LLM-generated output and the corresponding human-provided reference. Since there may exist several possible ground truth responses associated with one internal symbolic set and one instruction, we compute the performance for each pair by taking the maximum similarity across all human-provided references $G_{i,j,q}$. The similarity is high if at least one of the references provides a high similarity. The average score over K runs is defined as:

$$M_{i,j} = \frac{1}{K} \sum_{k=1}^{K} \max_{q=1\ldots Q} M\left(o_{i,j,k}^{\mathrm{LLM}}, G_{i,j,q}\right) \tag{6}$$

This formulation allows us to robustly evaluate the performance of LLMs to translate symbolic representations into interpretable language aligned with human expectations. The overall algorithmic procedure is described in Algorithm 2.

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