
Bridging Symbols from Language and Hierarchical Reinforcement Learning with Active Imitation

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Abstract

Large Language Models (LLMs) exhibit their potential for interacting with reinforcement learning (RL) agents, the main challenge is to align the world model learned by the agent with a representation compatible with LLMs. We solve this problem by proposing an algorithm named SGIM-STAR that creates online a discrete world representation by reinforcement learning exploration, it is a hierarchical RL method that augments STAR with a partition-wise, learning-progress-driven switch between a learned Q-learning Navigator and an LLM Navigator. The agent builds a discrete reachability-based partition online and uses intrinsic motivation to query the LLM only when beneficial, defaulting to the learned navigator otherwise. This yields usage cost-aware: the learned navigator 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 result demonstrates a practical fusion of LLMs with emerging symbolic world models 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 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

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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 from 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 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 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 successful 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 exemplified by GPT variants, Claude, and others, have significantly expanded their capabilities beyond natural language processing to complex reasoning and decision-making tasks. Recent studies have explored using LLMs as planners or controllers in robotic systems, highlighting their potential to exploit the internal world representations within LLMs. Hu et al. [2019] generates a plan in natural language, which is then executed by a separate model. Carta et al. [2025] introduced a hierarchical learning agent to continuously compile mastered goals into the low-level policy and coupled it with LLMs to serve as the top-level controller, exploiting its strengths in goal decomposition and generalization.

However, integrating LLMs into reinforcement learning frameworks remains challenging due to the discrepancy between the symbolic plans output by language and the continuous sensorimotor space. 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, the top-level policy can produce 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. 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 propose an algorithm for learning long-horizon tasks in the HRL framework with a high-level agent can choose actively its learning strategy between reinforcement learning or a LLM-based planner. The originality is that we use for both strategies a symbolic representation of the sensorimotor space, by learning an emergent symbolic representation, making it compatible with the symbolic space of language.

3 Methods

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.

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 spatial abstraction by analyzing k -step reachability relations between abstract goal regions.

3.2 Integration of an LLM into the Top Level Agent

We extend STAR by incorporating an LLM into the top-level agent. The structure is shown in Fig. 1. Instead of relying solely on the Navigator policy $\pi_{STAR}(G|s_t)$, we introduce an LLM-based planner

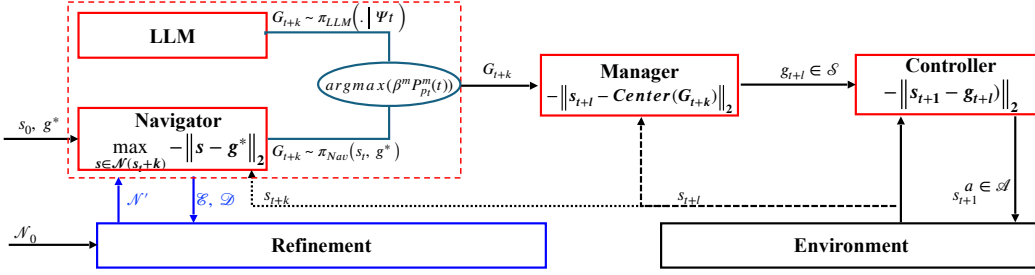


Figure 1: Algorithmic architecture of SGIM-STAR which integrates the LLM and the Navigator of STAR at the top level agent. The Navigator or the LLM selects subgoal regions $G \in \mathcal{G}$, while the middle-level manager and low-level controller are unchanged. The choice between the LLM and the Navigator.

$\pi_{LLM}(G|\Psi_t)$, 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:

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

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.

3.3 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 a progress measures as a selection mechanism.

Initialization. For the first N decision steps, the planner is chosen randomly between the STAR 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 :

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

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:

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

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

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.

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
1: \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
2: \forall region $p \in \mathcal{P}_0, \forall$ planner $m \in \mathcal{M}$, discounted progress scores $P_p^{(m)} \leftarrow 0$
3: $t \leftarrow 0$, observe s_0 and reward r_0
4: **while** episode not terminated **do**
5: $p_t \leftarrow \phi(s_t)$ ▷ Identify current region
6: **if** $t < N$ **then**
7: Choose $m(t) \sim \text{Uniform}(\mathcal{M})$ ▷ Warm-start randomization
8: **else**
9: Compute weighted scores in region p_t :
$$P_{p_t}^{(m)}(t) = \sum_{j=0}^n \alpha^j \Delta_{t-j}^{(m)}$$
$$m(t) \leftarrow \arg \max_{m \in \{\text{STAR}, \text{LLM}\}} \left\{ \beta^{(m)} P_{p_t}^{(m)}(t) \right\}$$

10: **end if**
11: Use planner $m(t)$ to select top-level region G_t and act for one decision step
12: Observe next state s_{t+1} and reward r_{t+1}
13: $\Delta_{t+1}^{(m(t))} \leftarrow r_{t+1} - r_t$ ▷ Incremental reward difference
14: Append $\Delta_{t+1}^{(m(t))}$ to buffer $\mathcal{B}_{p_t}^{(m(t))}$ (drop oldest if $|\mathcal{B}_{p_t}^{(m(t))}| > n+1$)
15: $t \leftarrow t + 1, r_t \leftarrow r_{t+1}, s_t \leftarrow s_{t+1}$
16: **end while**

4 Experiments

4.1 Experiment Setup

We evaluate our approach in the Ant environment, originally introduced by Duan et al. [2016] and later popularized in hierarchical reinforcement learning benchmarks by Nachum et al. [2018]. 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 top-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 the STAR Navigator 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 $\mathcal{P}_{p_t}^{(m)}$ 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.

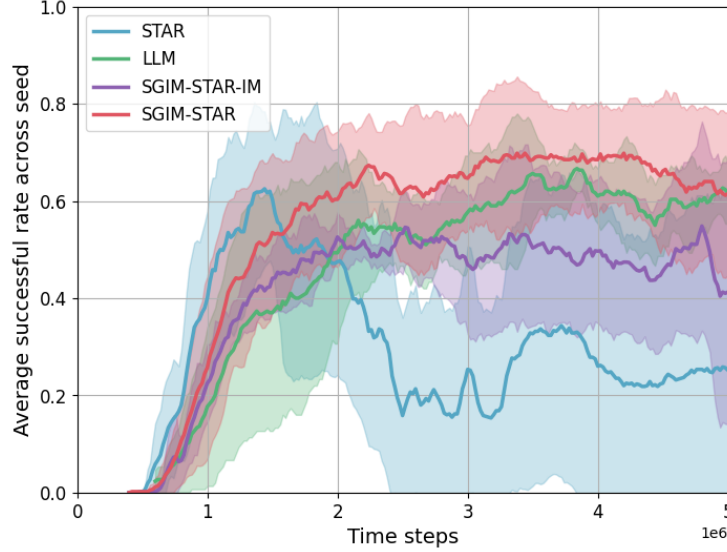


Figure 2: Average successful rate of four methods

4.2 Results and Analyses

Fig.2 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.3a). These results demonstrate that incorporating partitioned task structure and adaptively integrating LLM guidance produces superior resilience in this long-horizon task.

To further analyze stability, we examine individual training curves of each method. The pure RL baseline STAR, as shown in Fig.3a, 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 3b 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.3d 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.3c. This suggests that state-space partitioning plays a critical role in stabilizing long-horizon learning.

A key insight is that in SGIM-STAR the agent does not use the LLM uniformly throughout training, but rather 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.4a 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.

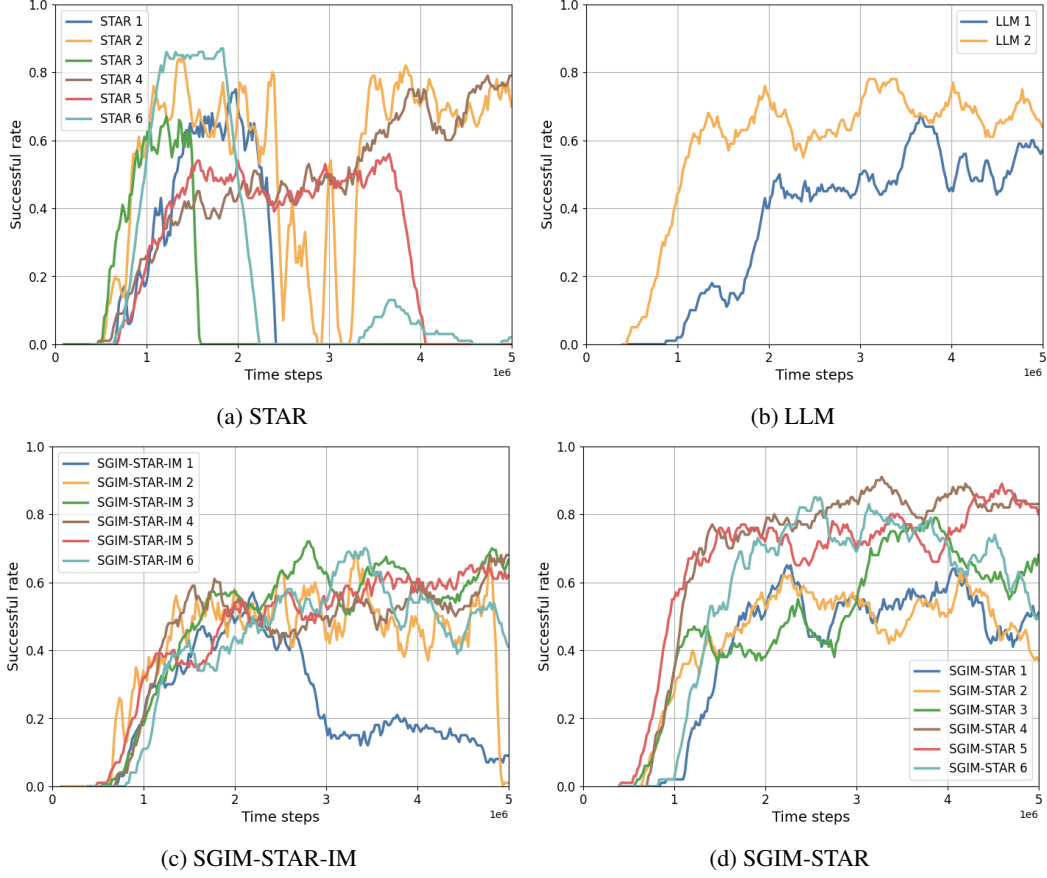


Figure 3: Successful rate of each run

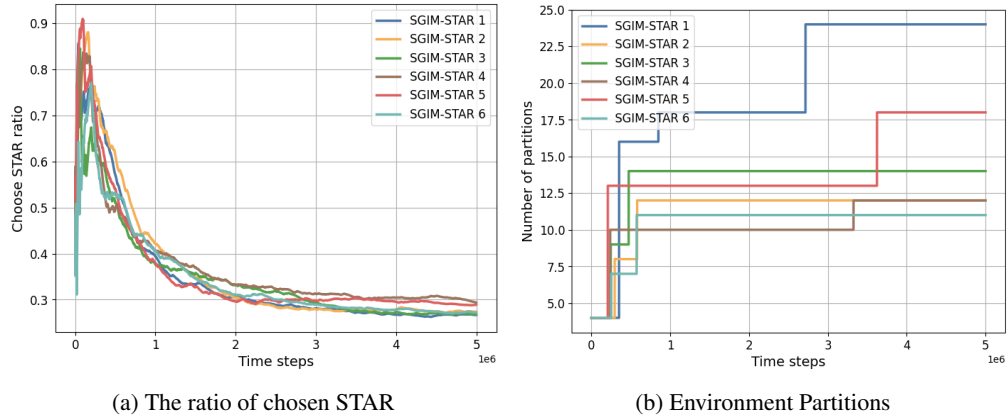


Figure 4: Adaptive choice of Planner by Partition

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.4b 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.

5 Discussion

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 intrinsically 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 STARL, then switch to LLM. The agent naturally relies more on the RL-based 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 enables to leverage LLMs to help the learning process of the agent.

6 Conclusion

We present *SGIM-STAR*, a simple, partition-wise-progress-based algorithm that switches between a learned STAR navigator and an LLM navigator. 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 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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References

- A. Baranes and P.-Y. Oudeyer. Active learning of inverse models with intrinsically motivated goal exploration in robots. *Robotics and Autonomous Systems*, 61(1):49–73, 2013. doi: 10.1016/j.robot.2012.05.008.
- T. Carta, C. Romac, L. Gaven, P.-Y. Oudeyer, O. Sigaud, and S. Lamprier. Herakles: Hierarchical skill compilation for open-ended llm agents, 2025. URL <https://arxiv.org/abs/2508.14751>.
- S. Chakraborty, K. Weerakoon, P. Poddar, M. Elnoor, P. Narayanan, C. Busart, P. Tokekar, A. S. Bedi, and D. Manocha. Re-move: An adaptive policy design for robotic navigation tasks in dynamic environments via language-based feedback. 03 2023. URL <https://arxiv.org/abs/2303.07622>.
- D. Driess, F. Xia, M. S. M. Sajjadi, C. Lynch, A. Chowdhery, B. Ichter, A. Wahid, J. Tompson, Q. Vuong, T. Yu, W. Huang, Y. Chebotar, P. Sermanet, D. Duckworth, S. Levine, V. Vanhoucke, K. Hausman, M. Toussaint, K. Greff, A. Zeng, I. Mordatch, and P. Florence. Palm-e: An embodied multimodal language model, 2023. URL <https://arxiv.org/abs/2303.03378>.

- Y. Duan, X. Chen, R. Houthoofd, J. Schulman, and P. Abbeel. Benchmarking deep reinforcement learning for continuous control. In *International conference on machine learning*, pages 1329–1338. PMLR, 2016.
- N. Duminy, S. M. Nguyen, J. Zhu, D. Duhaut, and J. Kerdreux. Intrinsically motivated open-ended multi-task learning using transfer learning to discover task hierarchy. *Applied Sciences*, 11(3), 2021.
- C. Finn, S. Levine, and P. Abbeel. Guided cost learning: Deep inverse optimal control via policy optimization. In M. F. Balcan and K. Q. Weinberger, editors, *Proceedings of The 33rd International Conference on Machine Learning*, volume 48 of *Proceedings of Machine Learning Research*, pages 49–58, New York, New York, USA, 20–22 Jun 2016. PMLR.
- J. Fu, K. Luo, and S. Levine. Learning robust rewards with adversarial inverse reinforcement learning. In *Proceedings of the 35th International Conference on Machine Learning (ICML)*, volume 80 of *Proceedings of Machine Learning Research*, 2018. URL <https://proceedings.mlr.press/v80/fu18a.html>.
- J. Gottlieb, P.-Y. Oudeyer, M. Lopes, and A. Baranes. Information-seeking, curiosity, and attention: computational and neural mechanisms. *Trends in Cognitive Sciences*, 17(11):585–593, 10 2013.
- H. Hu, D. Yarats, Q. Gong, Y. Tian, and M. Lewis. Hierarchical decision making by generating and following natural language instructions. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.
- D.-S. Jang, D.-H. Cho, W.-C. Lee, S.-K. Ryu, B. Jeong, M. Hong, M. Jung, M. Kim, M. Lee, S. Lee, and H.-L. Choi. Unlocking robotic autonomy: A survey on the applications of foundation models. *International Journal of Control, Automation and Systems*, 22(8):2341–2384, Aug 2024.
- Y. Jiang, S. S. Gu, K. P. Murphy, and C. Finn. Language as an abstraction for hierarchical deep reinforcement learning. In H. Wallach, H. Larochelle, A. Beygelzimer, F. d'Alché-Buc, E. Fox, and R. Garnett, editors, *Advances in Neural Information Processing Systems*, volume 32. Curran Associates, Inc., 2019.
- K. Jokinen. The need for grounding in LLM-based dialogue systems. In T. Dong, E. Hinrichs, Z. Han, K. Liu, Y. Song, Y. Cao, C. F. Hempelmann, and R. Sifa, editors, *Proceedings of the Workshop: Bridging Neurons and Symbols for Natural Language Processing and Knowledge Graphs Reasoning (NeusymBridge) @ LREC-COLING-2024*, pages 45–52, Torino, Italia, May 2024. ELRA and ICCL.
- W. B. Knox, P. Stone, and C. Breazeal. *Training a Robot via Human Feedback: A Case Study*, pages 460–470. Springer International Publishing, 2013.
- A. Levy, G. Konidaris, R. Platt, and K. Saenko. Learning multi-level hierarchies with hindsight. In *International Conference on Learning Representations*, 2019.
- S. Li, L. Zheng, J. Wang, and C. Zhang. Learning subgoal representations with slow dynamics. In *International Conference on Learning Representations (ICLR)*, 2021. URL <https://openreview.net/forum?id=wxRwhSdORKG>.
- Y. J. Ma, W. Liang, G. Wang, D.-A. Huang, O. Bastani, D. Jayaraman, Y. Zhu, L. Fan, and A. Anandkumar. Eureka: Human-level reward design via coding large language models. In *2nd Workshop on Language and Robot Learning: Language as Grounding*, 2023.
- O. Nachum, S. S. Gu, H. Lee, and S. Levine. Data-efficient hierarchical reinforcement learning. *Advances in neural information processing systems*, 31, 2018.
- S. M. Nguyen and P.-Y. Oudeyer. Interactive learning gives the tempo to an intrinsically motivated robot learner. In *IEEE-RAS International Conference on Humanoid Robots (Humanoids 2012)*, pages 645–652, 2012a.
- S. M. Nguyen and P.-Y. Oudeyer. Active choice of teachers, learning strategies and goals for a socially guided intrinsic motivation learner. *Paladyn, Journal of Behavioral Robotics*, 3(3):136–146, 2012b. doi: 10.2478/s13230-013-0110-z.
- P.-Y. Oudeyer and F. Kaplan. What is intrinsic motivation? a typology of computational approaches. *Frontiers in Neurobotics*, 1(6), 2007.
- P.-Y. Oudeyer, F. Kaplan, V. Hafner, and A. Whyte. The playground experiment: Task-independent development of a curious robot. In *Spring Symposium on Developmental Robotics*, pages 42–47. AAAI, 2005.
- C. O. Retzlaff, S. Das, C. Wayllace, P. Mousavi, M. Afshari, T. Yang, A. Saranti, A. Angerschmid, M. E. Taylor, and A. Holzinger. Human-in-the-loop reinforcement learning: A survey and position on requirements, challenges, and opportunities. *Journal of Artificial Intelligence Research*, 79:359–415, Jan. 2024.

- S. Ross, G. J. Gordon, and J. A. Bagnell. A reduction of imitation learning and structured prediction to no-regret online learning. In *Proceedings of the 14th International Conference on Artificial Intelligence and Statistics (AISTATS)*, pages 627–635, 2011. URL <https://proceedings.mlr.press/v15/ross11a.html>.
- J. Schmidhuber. Curious model-building control systems. In *Proc. Int. Joint Conf. Neural Netw.*, volume 2, pages 1458–1463, 1991.
- Y. Shentu, P. Wu, A. Rajeswaran, and P. Abbeel. From llms to actions: Latent codes as bridges in hierarchical robot contro. In *IROS*, 2024.
- A. Shon, D. Verma, and R. P. Rao. Active imitation learning. In *American Association for Artificial Intelligence*, volume 22, page 756. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999, 2007.
- M. Zadem, S. Mover, and S. M. Nguyen. Goal space abstraction in hierarchical reinforcement learning via set-based reachability analysis. In *2023 IEEE International Conference on Development and Learning (ICDL)*, pages 423–428, Nov 2023.
- M. Zadem, S. Mover, and S. M. Nguyen. Reconciling spatial and temporal abstractions for goal representation. In *The Twelfth International Conference on Learning Representations*, 2024.
- T. Zhang, S. Guo, T. Tan, X. Hu, and F. Chen. Generating adjacency-constrained sub-goals in hierarchical reinforcement learning. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2020. URL <https://proceedings.neurips.cc/paper/2020/hash/f5f3b8d720f34ebebceb7765e447268b-Abstract.html>. Spotlight.
- B. Zitkovich, T. Yu, S. Xu, P. Xu, T. Xiao, F. Xia, J. Wu, P. Wohlhart, S. Welker, A. Wahid, Q. Vuong, V. Vanhoucke, H. Tran, R. Soricut, A. Singh, J. Singh, P. Sermanet, P. R. Sanketi, G. Salazar, M. S. Ryoo, K. Reymann, K. Rao, K. Pertsch, I. Mordatch, H. Michalewski, Y. Lu, S. Levine, L. Lee, T.-W. E. Lee, I. Leal, Y. Kuang, D. Kalashnikov, R. Julian, N. J. Joshi, A. Irpan, brian ichter, J. Hsu, A. Herzog, K. Hausman, K. Gopalakrishnan, C. Fu, P. Florence, C. Finn, K. A. Dubey, D. Driess, T. Ding, K. M. Choromanski, X. Chen, Y. Chebotar, J. Carbajal, N. Brown, A. Brohan, M. G. Arenas, and K. Han. RT-2: Vision-language-action models transfer web knowledge to robotic control. In *7th Annual Conference on Robot Learning*, 2023.

Appendix

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
9 9 8 12 12 2 2 15 15 15 15 15
5 5 5 7 1 14 14 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
```

-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.

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