
Semantic HELM: An Interpretable Memory for Reinforcement Learning

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Abstract

Reinforcement learning agents deployed in the real world often have to cope with partially observable environments. Therefore, most agents employ memory mechanisms to approximate the state of the environment. Recently, there have been impressive success stories in mastering partially observable environments, mostly in the realm of computer games like Dota 2, StarCraft II, or MineCraft. However, none of these methods are interpretable in the sense that it is not comprehensible for humans how the agent decides which actions to take based on its inputs. Yet, human understanding is necessary in order to deploy such methods in high-stake domains like autonomous driving or medical applications. We propose a novel memory mechanism that operates on human language to illuminate the decision-making process. First, we use CLIP to associate visual inputs with language tokens. Then we feed these tokens to a pretrained language model that serves the agent as memory and provides it with a coherent and interpretable representation of the past. Our memory mechanism achieves state-of-the-art performance in environments where memorizing the past is crucial to solve tasks. Further, we present situations where our memory component excels or fails to demonstrate strengths and weaknesses of our new approach.

1 Introduction

In reinforcement learning (RL) an agent interacts with an environment and learns from feedback provided in the form of a reward function. In many applications, especially in real-world scenarios, the true state of the environment is not directly accessible to the agent, but rather approximated via observations that reveal mere parts of it. In such environments the capability to approximate the true state by virtue of an agent’s perception is crucial [119; 52]. To this end, many approaches track events that occurred in the past. The brute-force strategy is to simply store all past observations. However, this is often infeasible and it is much more efficient to store more abstract representations of the history. Thus, many RL algorithms use memory mechanisms such as LSTM [41] or Transformer [100] to compress sequences of high-dimensional observations. This has led to impressive successes mostly in the realm of mastering computer games on a human or even super-human level. Some examples are Dota 2 [12], StarCraft II [101], or MineCraft [10; 78].

Most state-of-the-art methods dealing with partial observability in RL are not interpretable [25]. This means that a human being cannot entertain or reenact the decision-making process of the agent. Yet, this is an essential requirement in order to deploy agents in high-stake domains like autonomous driving or medical applications [5]. An interpretable decision-making process promotes user trust and, therefore, increases acceptance if the system is able to sufficiently elucidate its decisions in

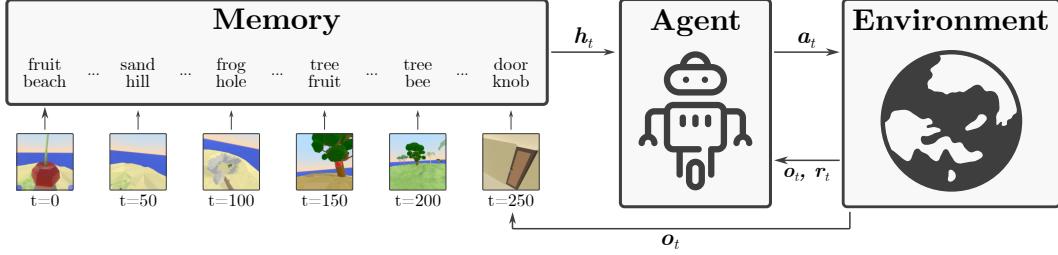


Figure 1: We add a semantic and interpretable memory to an agent to tackle partially observable RL tasks. We map visual observations o_t to the language domain via CLIP retrieval. The memory component, a pretrained language encoder, operates on text only and compresses a history of tokens into a vector h_t . The agent takes an action a_t based on the current observation o_t and the compressed history h_t . This enables interpretability of what the agent stores in its memory.

human-intelligible form to the user. If a self-driving car, e.g., explains “reducing speed due to children playing next to the lane” the user may reenact and challenge this decision by virtue of its own perception. Furthermore, interpretability facilitates accurate failure analysis which in turn enables improvement of system safety. This is particularly useful in the context of partially observable RL, where modular architectures are popular.

To shed light on the decision-making process, we draw inspiration from the semantic memory present in humans [111] and propose a memory mechanism based on human language. Humans memorize abstract concepts rather than every detail of information they encountered in the past [87; 14]. Their ability to abstract is heavily influenced by the exposure to language in early childhood [104]. Further, language is used on a daily basis to abstract and pass on information between humans. Therefore, language is a natural choice as a representation for compounding information and has the key advantage of being intrinsically interpretable. This enables analyzing if critical pieces of information have entered the memory or not. Based on this data, it becomes clear which parts of the system require refinement. Moreover, natural language has been shown to be effective as a compressed representation of past events in RL (HELM, [68]).

Our method leverages pre-trained foundation models to construct a memory mechanism that does not require any training. We use CLIP [84] to associate visual inputs with language tokens. Thereby, the vocabulary of the CLIP language encoder serves as a semantic database of concepts from which we retrieve the closest tokens to a given observation. These tokens are passed to a pretrained language model that serves as memory and provides the agent with a coherent representation of the past. This results in our new method Semantic HELM (SHELM).

We illustrate the importance of a interpretable and semantic memory in partially observable RL problems. First, we conduct a qualitative analysis on whether a CLIP vision encoder is capable of extracting semantics of synthetic environments. Then, we test SHELM on a set of 2D MiniGrid [20], and 3D MiniWorld [19] environments. We compare SHELM with strong memory-based baselines and find that these are often susceptible to random effects in the environment. Contrary, SHELM is much more robust and in turn reaches state-of-the-art performance on tasks that are unsolvable without a memory component. On more realistic 3D environments such as Avalon [4] and Psychlab [57], SHELM successfully extracts semantics of visual observations. In turn, SHELM attains state-of-the-art performance in a challenging Psychlab task requiring two orders of magnitude less interaction steps than prior methods. On Avalon we find that a semantic memory does not yield any benefits. In fact, we observe that agents with memory tend to learn faster, but match the final performance of a Markovian baseline.

2 Methods

Our goal is to express visual observations in language space such that the resulting representations become interpretable for humans. To this end, we instantiate a mapping from images to text in the form of pretrained components which are entirely frozen during training. This way the available computational resources are invested into performance rather than interpretability. Before we describe SHELM, we briefly review the HELM framework, which serves as a starting point for our work.

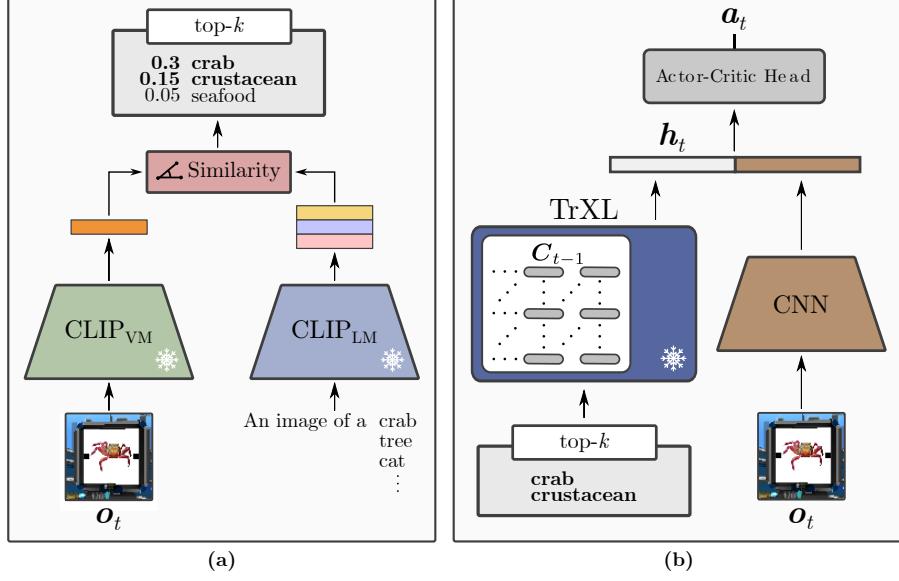


Figure 2: Architecture of SHELM. Given an observation \mathbf{o}_t we retrieve the top- k tokens present in the vocabulary of CLIP (a). Subsequently, these tokens are passed to the TrXL which represents the memory module of SHELM (b). \mathbf{c}_{t-1} represents the memory cache of the TrXL which tracks past tokens. Finally, the actor-critic head receives a compressed memory representation from the TrXL, as well as learned task-specific features from the CNN and outputs an action a_t .

2.1 Background

HELM [68] was proposed as a framework for RL in partially observable environments. It utilizes a pretrained LM as memory mechanism that compresses past observations. To map environment observations $\mathbf{o}_t \in \mathbb{R}^n$ to the LM it introduces the FrozenHopfield (FH) mechanism, which performs a randomized attention over pretrained token embeddings $\mathbf{E} = (\mathbf{e}_1, \dots, \mathbf{e}_k)^\top \in \mathbb{R}^{k \times m}$ of the LM, where k is the vocabulary size and m is the embedding dimension. Let $\mathbf{P} \in \mathbb{R}^{m \times n}$ be a random matrix with entries sampled independently from $\mathcal{N}(0, n/m)$. The FH mechanism performs

$$\mathbf{x}_t = \mathbf{E}^\top \text{softmax}(\beta \mathbf{E} \mathbf{P} \mathbf{o}_t), \quad (1)$$

where β is a scaling factor that controls the dispersion of \mathbf{x}_t within the convex hull of the token embeddings. This corresponds to a spatial compression of observations to a mixture of tokens in the LM embedding space. Since \mathbf{P} is random, the association of observations \mathbf{o}_t with token embeddings \mathbf{e}_i is arbitrary, i.e., not meaningful. That is, the FH mechanism does not preserve semantics. For temporal compression, HELM instantiates the LM with a pretrained TransformerXL (TrXL, 22) model. At time t , HELM obtains a compressed history representation by

$$\mathbf{h}_t = \text{TrXL}(\mathbf{c}_{t-1}, \mathbf{x}_t) \quad (2)$$

where \mathbf{c}_t represents the context cached in the memory register of TrXL up to timestep t .

More recent work has shown that the FH mechanism is prone to representation collapse if observations are visually similar to each other [69; 70]. They propose a new method, namely HELMv2, which substitutes the random mapping with a pretrained CLIP encoder. Subsequently, they adopt a batch normalization [48] with fixed shifting and scaling parameters to transfer the image embedding to the language space. Consequently, HELMv2 computes the inputs to the TrXL as

$$\mathbf{x}_t = \text{BN}_{\beta=\mu_E, \gamma=\sigma_E}(\text{CLIP}_{\text{VM}}(\mathbf{o}_t)), \quad (3)$$

where CLIP_{VM} denotes the CLIP vision model and μ_E and σ_E denote mean and standard deviation of the embedded vocabulary \mathbf{E} . This effectively fits the statistics of the image embeddings to those of the LM embeddings. Since the embedding spaces of CLIP and the LM were trained independently they are not semantically aligned. Therefore, also HELMv2 fails to preserve semantics of observations and, consequently, the memory mechanism of HELMv2 is not interpretable.

2.2 Semantic HELM

Semantic HELM (SHELM) inherits the high-level architecture from HELM but introduces some changes to the memory module. Similarly to HELMv2, we also use CLIP to embed environment observations. Instead of merely fitting the statistics of the respective embedding spaces we introduce a token-retrieval mechanism that preserves the semantics extracted by CLIP. The extracted tokens are then passed to the LM in the form of text and can be regarded as a textual description of environment observations.

In a first step, we determine the overlap of the token vocabularies of CLIP and the LM. Thereby, we obtain a set of tokens that can be directly transferred from the CLIP output embedding space to the LM input embedding space. We denote the set of these tokens as \mathcal{V} . CLIP usually requires a set of pre-defined text snippets to retrieve from. Instead of snippets, SHELM retrieves single tokens from \mathcal{V} . We augment each token in \mathcal{V} with a set of pre-defined prompts $\mathcal{P} = \{\mathbf{p}_1, \mathbf{p}_2, \dots\}$, where the size and contents of \mathcal{P} are hyperparameters of our method. We embed a token \mathbf{v} in the CLIP output space by computing the average embedding of its prompt augmentations. That is, we define the function

$$\text{embed}(\mathbf{v}) = \frac{1}{|\mathcal{P}|} \sum_{\mathbf{p} \in \mathcal{P}} \text{CLIP}_{\text{LM}}(\text{concat}(\mathbf{p}, \mathbf{v})). \quad (4)$$

We do this for every $\mathbf{v} \in \mathcal{V}$, which results in a set \mathcal{S} of CLIP-embedded tokens

$$\mathcal{S} = \{\text{embed}(\mathbf{v})\}_{\mathbf{v} \in \mathcal{V}}. \quad (5)$$

We denote by \max^k an extension of the max operator that returns the subset of the k largest elements in a set. For each observation we retrieve the k most similar tokens in terms of cosine similarity by

$$\mathcal{S}^* = \max_{\mathbf{s} \in \mathcal{S}}^k \frac{\mathbf{s}^\top \text{CLIP}_{\text{VM}}(\mathbf{o}_t)}{\|\mathbf{s}\| \|\text{CLIP}_{\text{VM}}(\mathbf{o}_t)\|}, \quad (6)$$

Finally, we embed single tokens \mathbf{v} corresponding to the set of tokens in \mathcal{S}^* in the LM embedding space and pass them to the LM. In this manner we provide the LM with a textual representation of the current observation. Like in HELM and HELMv2, we instantiate the LM with TrXL. Note that $k = |\mathcal{S}^*|$ is another hyperparameter of our method, namely the number of tokens that represent an observation. Effectively, k controls the degree of compression in the memory. By performing this procedure at every time step, we build up a human-readable representation of the history of the current episode. Another improvement over HELMv2 is that SHELM removes the restriction of HELMv2 that the embedding spaces of CLIP and LM must have the same dimensionality. In turn, any CLIP-like encoder can be used as semantic extractor for SHELM. A graphical illustration of the methodology of SHELM is depicted in Figure 2.

3 Experiments

First, we investigate in Section 3.1 whether CLIP can extract semantics of artificial scenes. Next, we train SHELM on four different environments, namely MiniGrid [20], MiniWorld [19], Avalon [4], and Psychlab [57]. We compare SHELM to HELMv2, LSTM (a recurrent baseline based on the LSTM architecture), and the popular Dreamerv2 agent [35]. To assess the dependence on memory we also add a Markovian baseline (PPO) in our experiments. We show that a semantic memory boosts performance in environments that are both heavily dependent on memory and photorealistic. Further, we demonstrate that Dreamerv2 especially suffers from random effects in the environment. SHELM on the other hand is much more robust to such effects. Finally, in Section 3.6 we perform ablation studies on the benefit of semantics and the trade-off between interpretability and performance.

We train all HELM variants with Proximal Policy Optimization (PPO, 92) on RGB observations. For training the Dreamerv2 baseline we use the original codebase¹ and train on RGB observations. We report results via IQM [2] and 95% bootstrapped confidence intervals (CIs) unless mentioned otherwise. We follow [21] and perform a Welch's t-test with a reduced significance level of $\alpha = 0.025$ at the end of training to test for statistical significance. We elaborate on the architectural design and hyperparameter sweeps in Appendix E.

¹<https://github.com/danijar/dreamerv2>

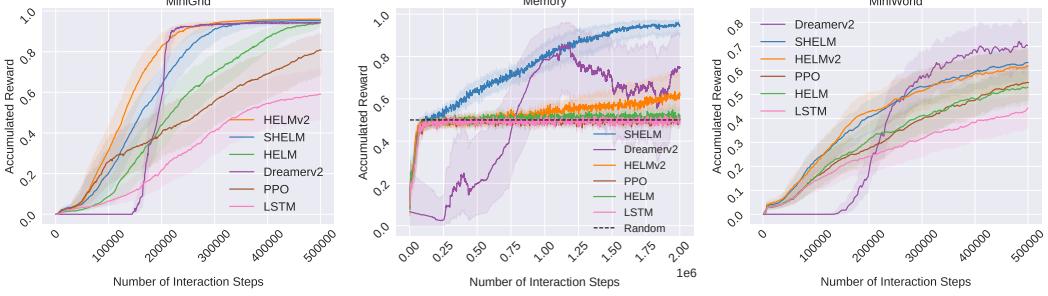


Figure 3: Performance of different methods on six MiniGrid environments (**left**), the MiniGrid-Memory task (**middle**) and eight MiniWorld tasks (**right**). We report IQM and 95% CIs across 30 seeds for each method.

3.1 Extracting semantics of virtual scenes

First, we investigate how much semantics, if any, CLIP vision encoders are able to extract from artificial scenes that are often encountered in RL environments. We compare the two smallest ResNet and ViT architectures, namely RN50 and ViT-B/16, since those add the least amount of computational overhead to SHELM. In this regard, we look at observations sampled via a random policy, propagate them through the CLIP vision encoder and retrieve the closest tokens in the CLIP embedding space according to the procedure described in Section 2.2. Figure 9 and Figure 8 in the appendix show token rankings for the MiniWorld and Avalon environments, respectively. We find that the retrieval of tokens strongly varies between vision encoder architectures. The differences are especially prominent for MiniWorld environments, where the ViT-B/16 encoder recognizes shapes and colors, whereas RN50 ranks entirely unrelated concepts highest. More photorealistic observations from the Avalon benchmark show a similar, but less prominent trend. We also observe a strong bias towards abstract tokens such as *screenshot*, *biome*, or *render*. We alleviate the retrieval of these tokens by including them in our prompts for retrieval. Therefore, instead of using the prompt “An image of a $\langle \text{tok} \rangle_n$ ”, we consider prompts such as “A screenshot of a $\langle \text{tok} \rangle_n$ ”, or “A biome containing a $\langle \text{tok} \rangle_n$ ”, where $\langle \text{tok} \rangle_n$ stands for the n -th token in \mathcal{V} . The full list of prompts for the different environments can be found in Table 1 in the appendix. Based on this analysis we use the ViT-B/16 encoder in combination with our designed prompts as semantics extractor for SHELM.

3.2 MiniGrid

We compare all methods on a set of six partially observable gridworld environments as in [68]. Additionally, we train on the MiniGrid-MemoryS11-v0 environment, which we refer to as Memory. The Memory task requires the agent to match the object in the starting room to one of the two objects at the end of a corridor. The agent’s view is restricted so it cannot observe both objects at the same time, therefore it needs to memorize the object in the starting room. If the agent chooses the wrong object at the end of the corridor, it receives no reward and the episode ends. The results across the six MiniGrid environments and the Memory environment are shown in Figure 3, left, and middle, respectively. In the Memory environment, SHELM significantly improves over the second-best method Dreamerv2 ($p = 0.011$). Figure 10 visualizes the tokens passed to the memory of a SHELM model after sampling episodes from a trained policy. SHELM primarily maps the ball to the token *miner*, and the key to the token *narrow*. Although the retrieved tokens do not represent the semantically correct objects in the observations, they are still easy to discriminate. Therefore, SHELM attains the highest performance by a wide margin. Furthermore, we find that Dreamerv2 is not robust to random changes in the environment, such as the randomly sampled starting object. We also observe this effect for another MiniGrid environment where random perturbations occur frequently (DynamicObstacles, Figure 14 in the appendix). On the other hand, SHELM and HELMv2 are much more robust to random changes in the environment. The LSTM baseline suffers from poor sample efficiency. Within the budget of 2M interaction steps defined for this experiment it does not perform better than randomly choosing a path at the end of the corridor. It requires more than twice as many interactions to solve the task (approximately 5M steps). While there is a significant improvement of SHELM over Dreamerv2 on the Memory environment, HELMv2 outperforms SHELM on the

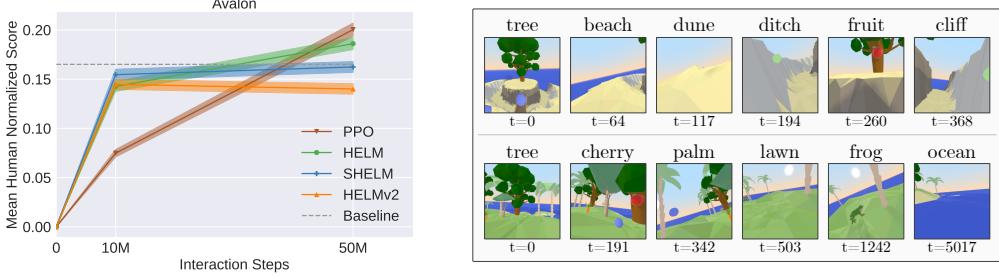


Figure 4: Mean and standard error of human normalized score across all tasks on the Avalon test worlds (**left**). Two sample episodes and their corresponding token mappings for episodes sampled from Avalon with a random policy (**right**).

remaining MiniGrid environments ($p = 0.001$). We hypothesize this is due to the lack of memory required to solve the tasks, since PPO is capable of solving all the tasks after longer training.

3.3 MiniWorld

The MiniWorld benchmark suite provides a set of minimalistic 3D environments. We select eight different tasks from MiniWorld and train all our methods on those (we clarify the selection criteria in Appendix A). A detailed description of the different MiniWorld tasks can be found in Appendix A. To the best of our knowledge we are the first to conduct a comprehensive evaluation across all environments in this benchmark. The results for MiniWorld are shown in Figure 3, right. Interestingly, Dreamerv2 outperforms SHELM on the MiniWorld environments ($p = 0.006$), even though semantics can be extracted from the 3D observations to some degree (see Figure 9 in the appendix). Again we observe the trend that Dreamerv2 fails entirely on environments containing random artifacts (Figure 14, in the appendix), whereas SHELM attains significantly better performance on such environments. This finding is corroborated by [81] who illustrate the robustness to noise of HELM-style memories compared to other recurrent baselines. Finally, LSTM again suffers from poor sample efficiency, performing worst out of all compared methods.

There are two potential reasons for the shortcoming of SHELM on the MiniWorld environments: (i) the tasks do not necessitate the use of a memory component, and (ii) the CLIP vision encoder fails to extract semantics from the visual observations. Our results on Memory suggest that SHELM improves performance on environments that are strongly dependent on a memory component, even when no semantics are transferred. Further, the PPO baseline is capable of solving all MiniWorld environments, and even exceeds performance of the LSTM baseline. This hints at a lack of memory dependency in order to solve the MiniWorld tasks.

3.4 Avalon

Avalon is an open-ended 3D survival game and environment designed for RL research consisting of 16 different tasks. The aim for the agent is to survive as long as possible by defending against or hunting animals and eating food to restore energy. An episode ends if the agent has no energy, receives environmental damage (e.g. from falling), or is being killed by a predator. The agent receives a dense reward as the difference in energy between consecutive timesteps, as well as a delayed reward upon successful completion of the task, i.e. eating food. The agent receives observations in the form of RGBD images, as well as proprioceptive input that comprise the delta in its position, position and deltas of its hands, its energy, etc. We adopt the same architecture and training strategy as [4] for all HELM variants. Specifically, we add the history compression branch to the baseline PPO agent and train on all 16 tasks, including their difficulty curriculum. The history compression branch is only based on RGB images and does not receive the proprioceptive state. The final performance of an agent is measured in terms of human normalized scores on a curated set of 1000 test worlds.

In addition to SHELM and HELMv2, we also train HELM and a Markovian baseline (PPO), which is identical to the PPO baseline in [4]. We show the mean human normalized score after 10M interaction steps and at the end of training at 50M interaction steps in Figure 4. For detailed results per task see Table 2 and Table 3 in the appendix. Remarkably, PPO reaches the highest average

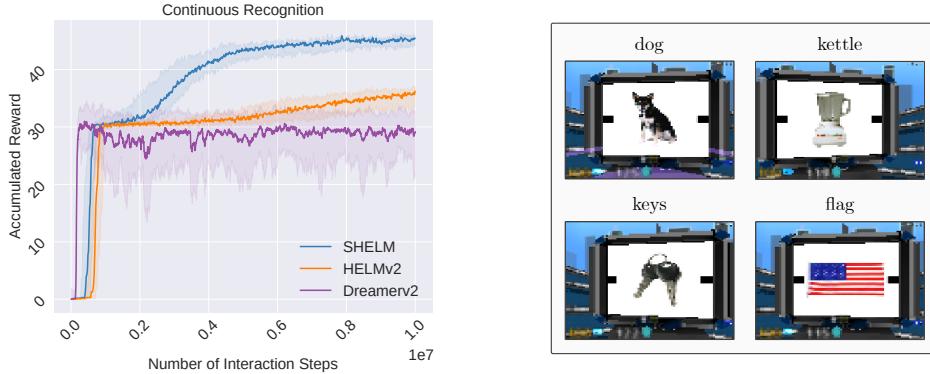


Figure 5: Performance for all methods on CR task from Psychlab. We report IQM and 95% CIs across 5 seeds (**left**). Observation and corresponding tokens for SHELM on CR environment (**right**).

score across all tasks, significantly exceeding the originally reported PPO baseline (0.165 ± 0.014). Moreover, our results for the PPO baseline are on-par with the reported performance of Dreamerv2 and our results for HELM. Interestingly, SHELM yields the highest performance on average after 10 M interaction steps, but merely yields slight improvements beyond that point. Most likely, this is due to the fact that we tuned our hyperparameters for only 10 M interaction steps due to limited computational resources. We surmise that the performance of SHELM and HELMv2 after 50 M interaction steps could be improved to match the performance of HELM and PPO by a more compute intensive tuning procedure. These results suggest that the memory component can be beneficial for a limited interaction budget, but does not provide any benefits in the long run. The benefit of SHELM, however, is that we can peak at its memory to identify failure cases. We show observations of two episodes and their token correspondences for SHELM in Figure 4. The observations are mostly mapped to semantically meaningful tokens. However, we also observe some failure cases which we show in Figure 11 in the appendix.

3.5 PsychLab

The Psychlab environment suite [57] consists of 8 complex tasks and was designed to probe RL agents for various cognitive abilities, including vision and memory. These tasks include, for example, probe recognition and cued recall testing of day-to-day objects. It leverages the synthetic 3D world of DMLab [11] where the agent is positioned on a platform facing a monitor. Depending on the task the monitor displays certain patterns or cues. We select the continuous recognition task (CR) to test the memory capabilities of SHELM. In this task the agent receives a stream of objects and has to identify whether it has seen a particular object before. We choose this particular environment because (i) it heavily relies on a memory component, and (ii) it provides photorealistic images of day-to-day objects. The latter is important since we rely on the capability of CLIP vision encoders in order to map observations to semantically correct text tokens. Since a multitude of objects are displayed on the screen within one episode this task extensively evaluates the memory capacity of an agent.

We train SHELM, HELMv2, and Dreamerv2 on the CR task (Figure 5). Our memory mechanism does not require any training, thus, we restrict our experiments to 10 million interaction steps. We observe that SHELM indeed learns to effectively utilize its memory within 10 M interaction steps and significantly outperforms both baselines. Prior works require interaction steps in the range of billions to converge to the optimal solution [72; 29]. Since these results are not publicly available and extremely costly to reproduce we did not include them in our results. HELMv2 also performs better than random (randomly choosing whether an object has occurred or not results in a reward around 30). Dreamerv2 is not able to exceed random performance within 10 M interaction steps as the objects to memorize are sampled randomly. As shown in previous experiments Dreamerv2 is susceptible to such random effects. Finally, we inspect the memory of SHELM and show the token mappings that are passed on to the memory module for some sample observations in Figure 5. In most cases SHELM assigns semantically correct tokens to the displayed objects. However, we also show some cases where the token retrieval of SHELM conflates different objects in Figure 12. We find that this can mostly be attributed to the low resolution of observations, since for higher resolution SHELM recovers from these failure cases (Figure 13).

3.6 Ablation Studies

We perform ablation studies to answer the following questions.

Are semantics important? We slightly alter the HELMv2 implementation from [69; 70] by retrieving the closest tokens in the language space after their frozen batchnorm layer, and finally passing those to the TrXL. This represents a setting similar to SHELM which receives tokens in the form of text, however, no semantics are preserved due to the arbitrary mapping to the language space. We call this setting HELMv2-Ret and train it on the Memory environment (see Figure 6). We find that if the mapping from observation to language does not transfer any semantic content, the performance drastically decreases.

Is it important to learn task-specific features?

Currently we always learn task-specific features by encoding the current timestep with a trainable CNN encoder. However, we could also encode the current timestep with the pretrained CLIP encoder. We call this setting SHELM-CLIP. An important consequence of this methodological change is that even features from the current observation can be interpreted by our retrieval mechanism. However, as shown in Figure 6, it is vital to learn task-specific features, as performance drastically drops for SHELM-CLIP.

Should the history branch operate on task-specific features?

To answer that question we substitute the CLIP encoder in the history branch with the learned CNN encoder (SHELM-CNN). We observe that SHELM-CNN is not capable of solving the Memory environment within the fixed interaction budget. A potential reason for this might be that essential features to solve the task must be learned before providing any useful information in the memory, thus, increasing the amount of required samples. Further, the TrXL might conflate the task-specific features since they differ from the input it has observed during training. Another immediate drawback of SHELM-CNN is the loss of interpretability, since we do not represent the observations in text form anymore. Thus, keeping abstract features in text-form should be preferred since that does not require any training and has the benefit of being interpretable.

Is a pretrained language encoder required? Here, we replace the TrXL with an LSTM operating on the retrieved tokens for history compression (SHELM-LSTM). This setting resulted in performance equivalent to randomly choosing an object at the end of the corridor. However, we believe that after longer training SHELM-LSTM can eventually learn to solve the task. This is supported by the fact that the simple LSTM baseline required approximately 5 M interaction steps to solve the same task. Nonetheless, the simpler and more sample efficient method is to maintain the frozen pretrained encoder instead of learning a compressed representation.

4 Related Work

RL and partial observability Reinforcement Learning with incomplete state information necessitates a memory for compressing the history an agent encountered. A plethora of prior works have used history compression to tackle credit assignment [8; 78; 106; 42], and partial observability [36; 101; 12; 80]. The memory maintained by an agent can either be external [40; 105], or directly integrated into the feature extraction pipeline via the network architecture. An orthogonal approach for history compression is training recurrent dynamics models [33; 75; 34; 35]. [77] provide a theoretical framework for analyzing RL algorithms that leverage memory-based feature abstraction.

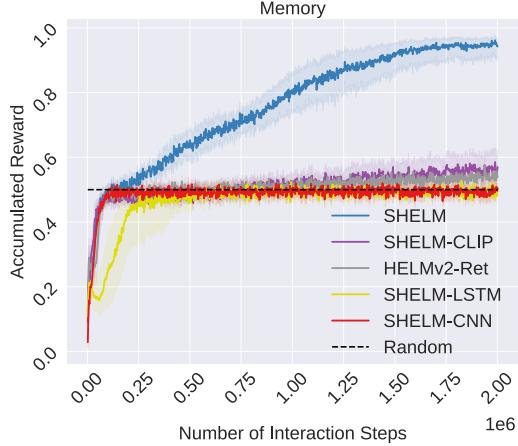


Figure 6: Ablation study on the effect of semantics and the influence of task-specific features. IQM and 95% CIs across 30 seeds on the MiniGrid-Memory task.

Other works investigated the question of what information to store in a stream of observations [91; 90; 115; 54; 93; 89]. We believe language is very well suited as medium for compression to summarize past events, as shown by [68].

Language in RL Language provides useful abstractions for Reinforcement Learning. These abstractions can be leveraged to represent high-level skills [96; 51; 49]. [40] ground language descriptors to visual observations in an external memory component to enable one-shot generalization. LMs have been used to improve exploration in text-based environments [110], or in visual environments by a language oracle [64]. Multimodal models pretrained with language supervision provide abstract embedding spaces that can be used for exploration in visual environments [99]. We leverage pretrained multimodal models to spatially compress visual observations to language tokens. Furthermore, pretrained LMs were leveraged for initializing policies in text-based environments [59], grounding to various environments [7; 45; 18], sequence modeling in the offline RL setup [86], and generating high-level plans [44; 46; 103; 97; 47; 60; 23; 26; 95; 3; 114]. [109] train an agent to caption virtual scenes from human demonstrations which enables manipulating and describing novel objects. Additionally, language has been used for augmenting the reward function [102; 9; 32; 17; 55], or learning a dynamics model [117; 116; 118; 108]. Closely related to our work [74], leverage LMs to impersonate agents based on a memory stream containing different levels of abstraction. Importantly, all agent-environment interactions in their work are conducted via a language interface, while our agent operates on visual inputs.

Language for Interpretability While there are a large number of explainable AI (XAI) methods to interpret predictions of supervised and unsupervised methods, interpretability methods in RL are scarce. Furthermore, the vast majority of interpretability approaches in RL follow a post-hoc approach [82]. Post-hoc approaches analyze the model after training, typically by creating a simpler surrogate model to provide explanations for the original model. In this regard, a plethora of prior works had used language as human interpretable medium to explain classification decisions in computer vision [37; 38; 73; 113; 39], or in natural language processing [6; 112; 16; 85; 65]. In contrast, intrinsically interpretable models are designed to be inherently interpretable even during training time. Our proposed method belongs to the category of intrinsically interpretable methods. Intrinsically interpretable models are preferable over post-hoc approaches in high-stake domains [88]. Intrinsically interpretable methods often restrict the complexity of the model class, which in turn results in reduced performance of the agent. Therefore, [31] propose to adopt a modular approach to interpretability. To this end, our work focuses on the memory module. This enables us to provide some extent of intrinsic interpretability while exceeding performance of state-of-the-art (non-interpretable) methods on memories that necessitate memory.

Foundation Models The advent of the Transformer architecture [100] gave rise to foundation models. Foundation models [13], such as GPT-3 [15], demonstrated remarkable few-shot capabilities. As shown by [79; 98; 53; 62], pretrained LMs can learn abstract symbolic rules and show sparks of reasoning. We leverage their abstraction capabilities for history compression in RL. Naturally, interest has sparked in combining vision and text data during pretraining [58; 94]. This finally resulted in large-scale multi-modal models, such as CLIP [84], or ALIGN [50]. Such vision FMs have been demonstrated to be well adaptable to foreign domains [1; 27; 66; 71]. We use CLIP to obtain language tokens that semantically correspond to concepts present in synthetic environments.

5 Reproducibility Statement

We make all our code and random seeds used in our experiments, as well as obtained results publicly available at <https://github.com/ml-jku/helm>. The pretrained language encoder, as well as the pretrained CLIP encoder are publicly available on the huggingface hub [107].

6 Conclusion

In many real-world scenarios an agent requires a memory mechanism to deal with partial observability. Current approaches to memory in RL are not interpretable for humans. Yet, interpretability is crucial to enable deployment of memory-based agents in real world applications. We advocate for the use of human language as an interpretable medium for abstraction of past information. We proposed

a new method called Semantic HELM, which maps environment observations to human-readable language tokens and showed compelling evidence that even for synthetic environments our memory mechanism can extract semantics from visual observations. Further, SHELM outperforms strong baselines on complex memory-dependent environments through its interpretable memory module. In cases where semantics cannot be extracted from observations, the cause can be investigated by inspection of SHELM’s memory module, which facilitates systematic troubleshooting. Even in such cases, SHELM mostly performs on-par with other memory-based approaches. Competitors, such as Dreamerv2, are often susceptible to random perturbations in the environment, while SHELM is much more robust to noise and excels in such environments. Finally, our experiments show that partially observable environments often do not necessitate a memory component, and can be solved by a Markovian policy. However, the addition of a memory component can facilitate sample efficiency.

Our semantic mapping is limited by the inherent ability of CLIP vision encoders to extract semantically meaningful features in synthetic environments. However, CLIP suffers from the modality gap [61], i.e., a misalignment between image and text modalities. In the future we aim at incorporating methods that mitigate the modality gap in our framework as well [30; 67]. Furthermore, we believe that the interpretability of our method can be enhanced even more by generating full captions from history observations instead of a small number of tokens. This could enable (i) a long-term memory with different levels of abstraction that textually summarizes all captions of corresponding observations similar to [83], (ii) a potential for planning in form of text from visual observations similar to [76], (iii) modeling dynamics of an environment in language space, and (iv) incorporating safety constraints on what aspects should be stored in the memory via human instructions as in [43].

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A Environments

We choose 8 diverse 3D environments of the MiniWorld benchmark suite:

- **CollectHealth:** The agent spawns in a room filled with acid and must collect medikits in order to survive as long as possible.
- **FourRooms:** The agent must reach a red box that is located in one of four interconnected rooms.
- **MazeS3Fast:** A procedurally generated maze in which the agent needs to find a goal object.
- **PickupObjs:** Several objects are placed in a large room and must be collected by the agent. Since the agent receives a reward of 1 for each collected object, the reward is unbounded.
- **PutNext:** Several boxes of various colors and sizes are placed in a big room. The agent must put a red box next to a yellow one.
- **Sign:** The agent spawns in a U-shaped maze containing various objects of different colors. One side of the maze contains a sign which displays a color in written form. The aim is to collect all objects in the corresponding color.
- **TMaze:** The agent must navigate towards an object that is randomly placed at either end of a T-junction.
- **YMaze:** Same as TMaze, but with a Y-junction.

We neglect the OneRoom and the Hallway environments, since those are easily solved by all compared methods. Further, we neglect the Sidewalk environment since it is essentially the same task as Hallway with a different background. Since the rewards of PickupObjs and CollectHealth are unbounded, we normalize them to be in the range of [0, 1], which is the reward received in all other environments. For a more detailed description of the MiniGrid environments we refer the reader to [68].

B Token Retrieval for Synthetic Environments

Since we perform retrieval on a token level we investigate the effect of augmenting tokens with different prompts, and the effect of different vision encoders on retrieval performance. We analyse the former at the example of the Avalon environment. Figure 7 shows some examples. We observed that simply encoding single tokens in CLIP space results in a bias toward abstract tokens such as *biome*, or *screenshot*. The same occurs for using the prompts originally used for zero-shot classification on the ImageNet dataset² [24]. However, one can alleviate this bias by including these frequently retrieved tokens in the prompt itself (see Figure 7, bottom). However, we found this strategy to be effective only for Avalon and Psychlab environments. The sets of prompts for both environments can be found in Table 1. For MiniGrid and MiniWorld we retrieve single tokens without any prompt.

Next, we investigate the influence of the choice of vision encoder architecture, e.g., RN50 vs ViT-B/16. We only consider those encoders since they induce the least complexity on our history compression pipeline. We show the closest tokens in CLIP space for observations of MiniWorld (see Figure 9) and Avalon environments (see Figure 8). For MiniWorld, CLIP can extract shapes and colors of very minimalistic shapes. However, the retrievals are very noisy, which is mirrored in the attained score of SHELM. For Avalon, however, the token retrievals are more convincing. Generally, we find that retrievals using the RN50 encoder of CLIP tend to be more noisy than retrieval utilizing a ViT-B/16 encoder.

C Qualitative Analyses

We show token mappings for the memory mechanism of SHELM to identify potential failures and successes. Figure 10 shows a few sample episodes from a trained policy on the Memory environment. Clearly, CLIP is not capable of extracting semantics of the abstract 2D gridworld environments. Thereby, it maps the ball to the token *miner* and the key to the token *narrow*. For minimalistic 3D environments, CLIP is capable of extracting colors and shapes of objects as can be seen in Figure 9. However, these results are still uninspiring since the token retrievals are very noisy.

²available at <https://github.com/openai/CLIP/tree/main>

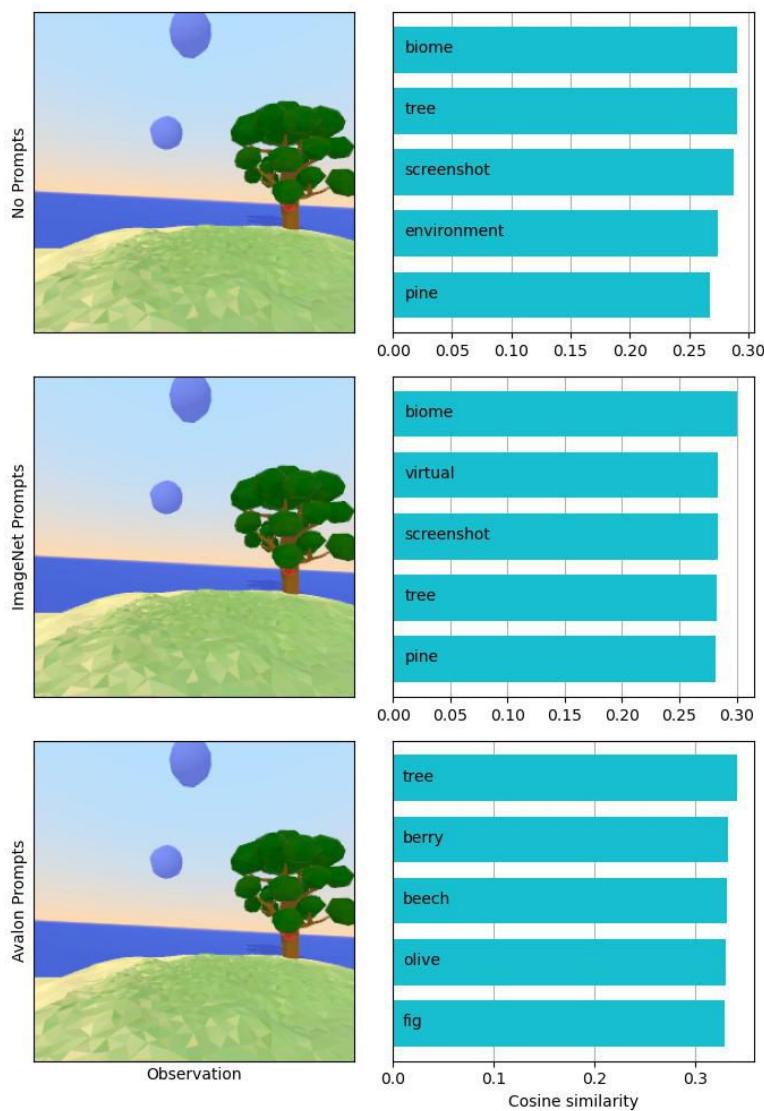


Figure 7: Token rankings for ViT-B/16 encoder of CLIP on Avalon observations. Tokens are encoded with the CLIP language encoder without prompt (**top**), with ImageNet specific prompts (**middle**), or prompts designed for Avalon (**bottom**).

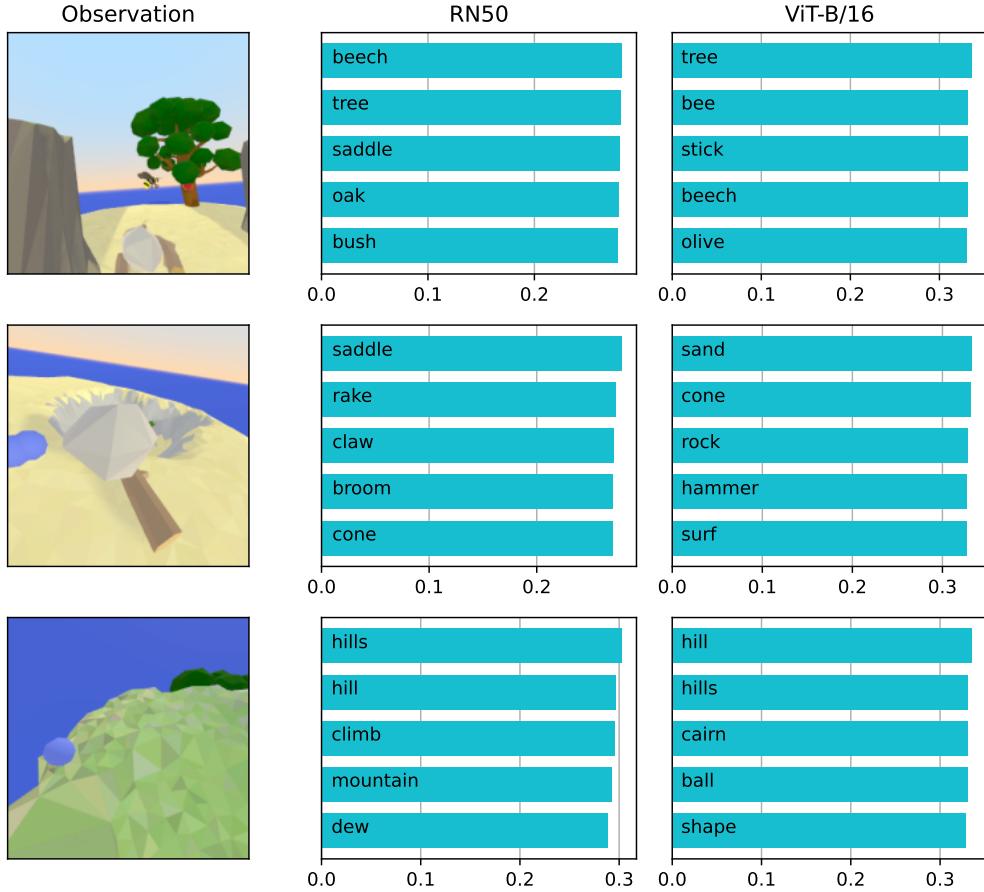


Figure 8: Token rankings for RN50 and ViT-B/16 encoders of CLIP on Avalon observations.

We also visualize episodes collected by a random policy from the Avalon environment in Figure 11. As opposed to the minimalistic MiniGrid and MiniWorld environments, CLIP successfully extracts semantically meaningful concepts which are subsequently passed to the memory. There are still some failure cases though. For example, in the second episode the agent is attacked by a bee. The feelers of the bee are mistaken for a *sword* as the bee moves into close proximity of the agent. Further after the agent successfully defends itself against the bee, it mistakes the dead bee for a *crab*. Intuitively, CLIP cannot correctly extract the concept of a dead bee in Avalon, since it has never encountered that during its pretraining stage. Alleviating such failure cases would require grounding CLIP to the respective environment as was done in [28].

Further, we visualize token mappings for objects the agent encounters in the continuous recognition task of Psychlab in Figure 12. The majority of token retrievals are semantically correct. However, sometimes the agent confuses different objects or conflates to the same token for different objects. An example for that are two middle objects in row 4 which are both mapped to the token *icon*, or the first two objects in row 6 that are mapped to the token *tuber*. We suspect that this occurs due to downscaling to a lower resolution which is conducted within the DMLab engine. Indeed, when taking a closer look at token retrievals at a higher resolution, they are mapped to different tokens (see Figure 13). Therefore, we consider two different aspects on how to alleviate this issue, (i) increasing the resolution of the observations and (ii) retrieving more than one token for an observation. The former results in increased computational complexity, which we aim to avoid, since the task is computationally very expensive already. The latter assumes that the retrieval differs at least in their top- k most likely tokens and is a viable solution.

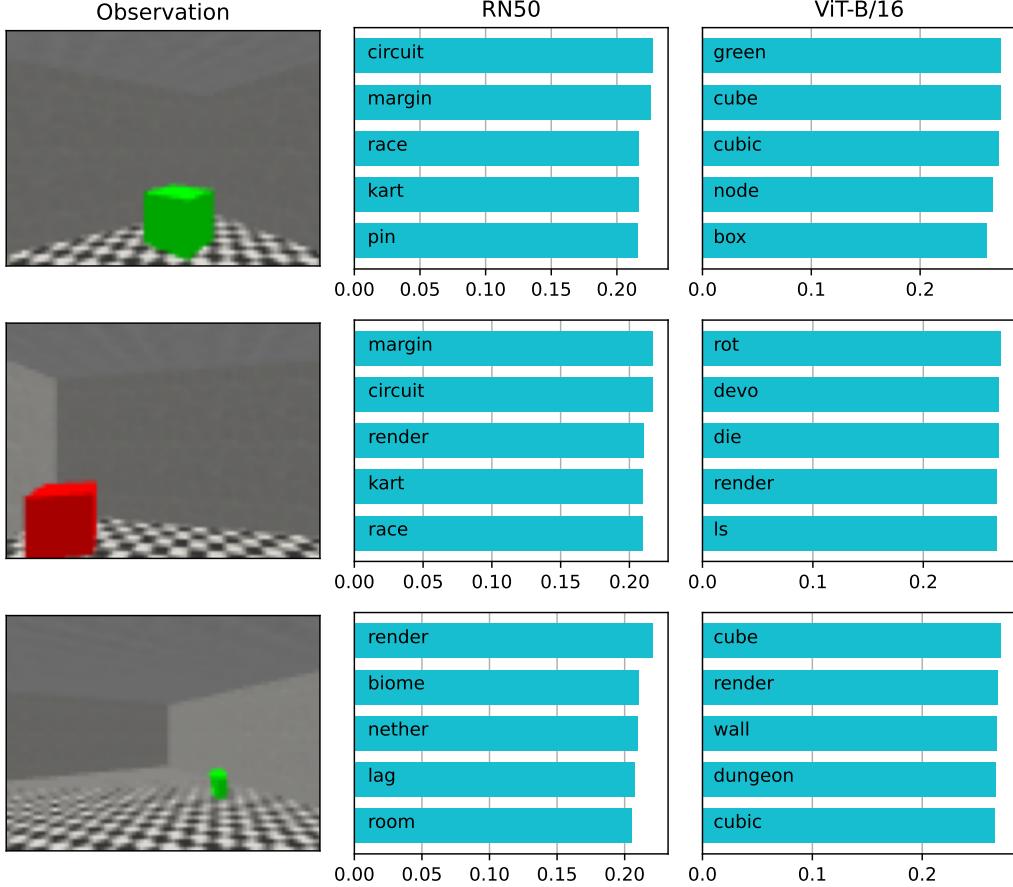


Figure 9: Token rankings for RN50 and ViT-B/16 encoders of CLIP on MiniWorld observations.

D Additional Results

We show results for PPO, HELM, HELMv2, and SHELM on all Avalon tasks after 10 M and 50 M interaction steps in Table 2 and Table 3, respectively. The addition of the history branch in HELM results in a significantly higher mean human normalized score after 10 M training steps ($p = 7.45\text{e-}29$). SHELM attains the highest score on average after 10 M timesteps. However, there is no significant difference between the HELM variants. After 50 M interaction steps we observe a drastic improvement for the PPO baseline, whereas performance of HELMv2 and SHELM stagnates. Since SHELM is demonstrably capable of extracting semantics from Avalon environments (see Figure 11), we believe that the main reason for these results is that the Avalon tasks do not really require the agent to use its memory.

E Hyperparameters and Training Details

Since the memory component of SHELM does not need to be trained, our memory requirements are comparably low. All our experiments were run on either a single GTX1080Ti or a single A100 GPU. The time requirements of our experiments vary for each environment. For MiniGrid and MiniWorld one run takes approximately two hours, while for Psychlab one run requires two days. These experiments were run on a single GTX1080Ti. Avalon is the most expensive environment in terms of compute. For Avalon, we used a single A100 for training where one run to train for 50 M interaction steps takes approximately three days.

Environment	Prompts
Avalon	a screenshot of
	a screenshot of a
	a screenshot of many
	a biome containing
	a biome containing a
	a biome containing many
Psychlab	a biome full of
	a render of
	a render of a
	a screenshot of
	a screenshot of a
	a screen showing
	a screen showing a

Table 1: Prompts used for token retrieval for the Avalon and Psychlab environments.

Task	PPO	HELM	HELMv2	SHELM
eat	0.518 ± 0.062	0.671 ± 0.071	0.714 ± 0.063	0.693 ± 0.071
move	0.132 ± 0.042	0.277 ± 0.068	0.294 ± 0.061	0.291 ± 0.063
jump	0.121 ± 0.040	0.232 ± 0.058	0.219 ± 0.051	0.217 ± 0.050
climb	0.051 ± 0.026	0.125 ± 0.039	0.211 ± 0.052	0.118 ± 0.038
descend	0.098 ± 0.036	0.184 ± 0.044	0.108 ± 0.035	0.202 ± 0.048
scramble	0.091 ± 0.037	0.213 ± 0.052	0.301 ± 0.056	0.271 ± 0.058
stack	0.022 ± 0.015	0.058 ± 0.029	0.075 ± 0.031	0.115 ± 0.041
bridge	0.026 ± 0.021	0.046 ± 0.026	0.040 ± 0.024	0.028 ± 0.018
push	0.014 ± 0.012	0.069 ± 0.030	0.069 ± 0.029	0.110 ± 0.044
throw	0.006 ± 0.008	0.017 ± 0.020	0.000 ± 0.000	0.000 ± 0.000
hunt	0.079 ± 0.033	0.077 ± 0.033	0.091 ± 0.034	0.091 ± 0.039
fight	0.078 ± 0.033	0.189 ± 0.048	0.207 ± 0.062	0.185 ± 0.051
avoid	0.037 ± 0.021	0.192 ± 0.047	0.211 ± 0.045	0.227 ± 0.050
explore	0.110 ± 0.038	0.194 ± 0.051	0.191 ± 0.050	0.204 ± 0.052
open	0.051 ± 0.028	0.134 ± 0.042	0.040 ± 0.024	0.102 ± 0.038
carry	0.024 ± 0.015	0.101 ± 0.041	0.073 ± 0.030	0.054 ± 0.027
navigate	0.009 ± 0.000	0.000 ± 0.000	0.000 ± 0.003	0.006 ± 0.008
find	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000
survive	0.032 ± 0.015	0.066 ± 0.005	0.041 ± 0.013	0.051 ± 0.016
gather	0.006 ± 0.010	0.008 ± 0.019	0.009 ± 0.007	0.006 ± 0.003
overall	0.075 ± 0.007	0.143 ± 0.010	0.145 ± 0.010	$\mathbf{0.149 \pm 0.011}$

Table 2: Mean human normalized score for all Avalon tasks for PPO, HELMv2, and SHELM after 10M interaction steps. We show mean and standard deviations.

MiniGrid and MiniWorld We adapt the hyperparameter search from [68]. Particularly, we search for learning rate in $\{5e-4, 3e-4, 1e-5, 5e-5\}$, entropy coefficient in $\{0.05, 0.01, 0.005, 0.001\}$, rollout length in $\{32, 64, 128\}$ for SHELM. To decrease wall-clock time of HELM variants, we vary the size of the memory register of TrXL such that it can fit the maximum episode length. We lower the number of interaction steps for the gridsearch if we observe convergence before the 500k interaction steps. If no convergence is observed within the 500K interaction steps, we tune for the entire duration. We apply the same scheme for tuning the LSTM baseline and tune the same hyperparameters as in [68].

Avalon After visual inspection of token retrievals for observations we found that there is no substantial difference in retrieved tokens for observations in close proximity to each other. Therefore,

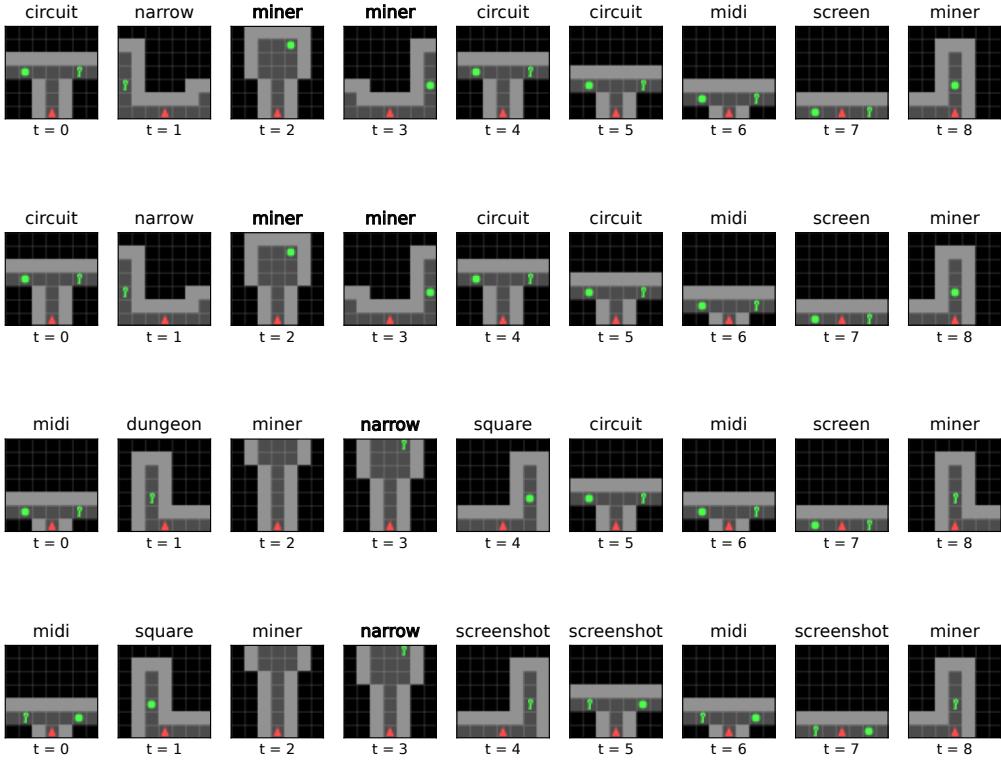


Figure 10: Episodes sampled for a trained SHELML policy on the MiniGrid-MemoryS11-v0 environment. The object *ball* is consistently mapped to the token *miner*, while the object *key* maps to the token *narrow*.

we introduce an additional hyperparameter, namely *history-frameskip*. Note that the history-frameskip is not functionally equivalent to the commonly used frameskip in, e.g., [63]. Rather, we actually discard frames within the skip. For example, for a history-frameskip of 10 the agent only observes the first and the eleventh frame in the history branch. The current branch observes every timestep as usual. We search over history-frameskip in $\{3, 5, 10\}$ and adapt the memory of the agent to $\{256, 128, 64\}$ timesteps respectively. Further we search over learning rate in $\{2.5e-4, 1e-4, 7e-5\}$, and the number of retrieved tokens in $\{1, 2, 4\}$. If an observation is represented as more than one token, this effectively reduces the number of observations that fit into the memory register of TrXL, and thereby introduces a recency bias. Hyperparameters for baselines are taken from [4]. We used their respective codebase to run our experiments.³

PsychLab Due to the computational complexity of the Psychlab environments we only run a gridsearch over the learning rate in $\{5e-4, 3e-4, 1e-4, 5e-5\}$, and the number of tokens that represent an observation in $\{1, 2, 4\}$. When using more than one token increase the memory register of TrXL accordingly, to fit the same context. Further we use 64 actors and set the rollout size to 256. For SHELML on continuous-recognition we only retrieve the closest token for an observation.

F Limitations

A current limitation of SHELML is time complexity. The rollout phase is particularly expensive since each timestep needs to be propagated through the TrXL. A potential solution for decreasing the

³<https://github.com/Avalon-Benchmark/avalon>

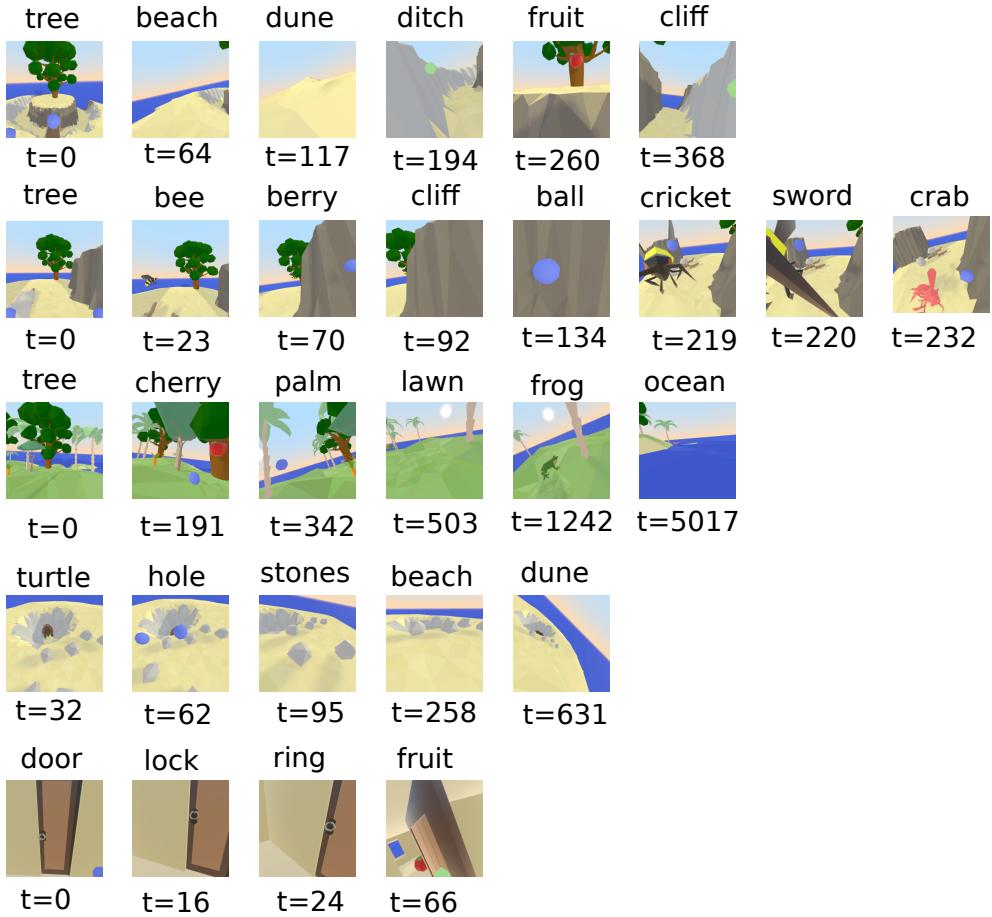


Figure 11: Episodes sampled from a random policy on various Avalon tasks.

complexity of the rollout phase would be distilling knowledge from the language model into smaller actor networks that interact with the environment as in [72]. Another option may be decreasing the complexity of the TrXL by pruning layers. However, this might negatively affect performance on the downstream tasks. A more fruitful avenue might be language encoders that are lower in complexity, such as ALBERT [56]. Although SHELM suffers from a time intensive rollout phase, we want to stress that it is still more efficient than, e.g., Dreamerv2. This is due to the fact that the memory mechanism is kept frozen. Therefore, the update phase does not require backpropagation through the memory component which results in a substantial speedup.

G Potential Negative Societal Impact

Our method relies on the use of FMs, which are trained on non-curated datasets which were crawled from the web. Therefore, these models readily reflect the biases and prejudices found on the web and, consequently, so might the resulting RL agent trained by our method. Finally, deploying RL agents in the real world can potentially cause damage if they are not carefully shepherded. Deployment in the real world however requires a carefully designed interface that allows the execution of selected actions by our agent.



Figure 12: Sample observations for continuous recognition task of Psychlab. The agent must swipe in a certain direction depending on whether it has encountered an object before in the same episode.

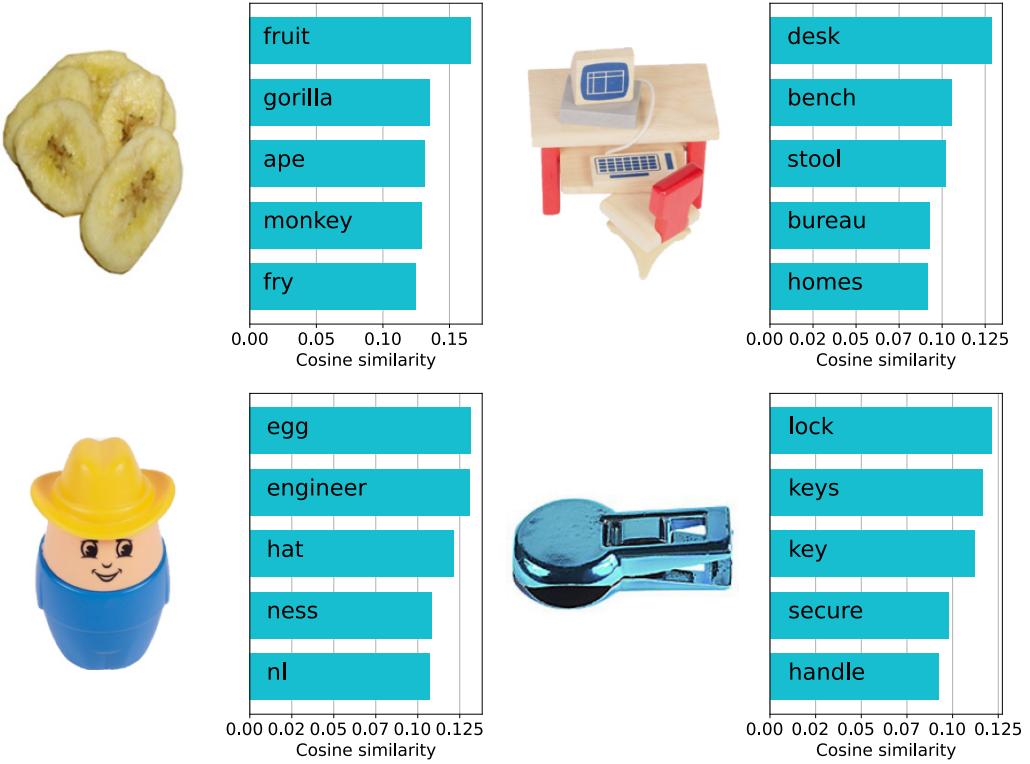


Figure 13: Top-5 token retrievals for objects that are conflated by SHELIM at a lower resolution. For higher resolution CLIP successfully maps the objects to different tokens.

Task	PPO	Dreamerv2	HELM	HELMv2	SHELIM
eat	0.889 ± 0.074	0.664 ± 0.065	0.925 ± 0.075	0.690 ± 0.064	0.833 ± 0.075
move	0.421 ± 0.078	0.364 ± 0.071	0.373 ± 0.076	0.266 ± 0.058	0.288 ± 0.059
jump	0.288 ± 0.065	0.234 ± 0.058	0.309 ± 0.059	0.196 ± 0.048	0.233 ± 0.056
climb	0.257 ± 0.052	0.227 ± 0.051	0.207 ± 0.049	0.130 ± 0.042	0.046 ± 0.176
descend	0.205 ± 0.056	0.290 ± 0.058	0.226 ± 0.051	0.155 ± 0.041	0.206 ± 0.044
scramble	0.496 ± 0.068	0.422 ± 0.058	0.352 ± 0.063	0.238 ± 0.052	0.311 ± 0.058
stack	0.083 ± 0.036	0.126 ± 0.043	0.079 ± 0.032	0.077 ± 0.032	0.096 ± 0.038
bridge	0.051 ± 0.028	0.121 ± 0.045	0.021 ± 0.018	0.027 ± 0.019	0.045 ± 0.025
push	0.138 ± 0.048	0.160 ± 0.043	0.118 ± 0.043	0.068 ± 0.028	0.125 ± 0.041
throw	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000	0.000 ± 0.000
hunt	0.032 ± 0.024	0.063 ± 0.028	0.062 ± 0.030	0.058 ± 0.029	0.052 ± 0.026
fight	0.292 ± 0.071	0.336 ± 0.076	0.219 ± 0.058	0.244 ± 0.059	0.193 ± 0.054
avoid	0.383 ± 0.091	0.515 ± 0.118	0.320 ± 0.062	0.236 ± 0.082	0.187 ± 0.044
explore	0.222 ± 0.059	0.190 ± 0.048	0.254 ± 0.061	0.171 ± 0.046	0.219 ± 0.050
open	0.053 ± 0.026	0.126 ± 0.041	0.096 ± 0.034	0.113 ± 0.039	0.117 ± 0.040
carry	0.122 ± 0.049	0.066 ± 0.028	0.085 ± 0.037	0.076 ± 0.032	0.095 ± 0.042
navigate	0.009 ± 0.010	0.000 ± 0.000	0.003 ± 0.005	0.000 ± 0.000	0.009 ± 0.011
find	0.000 ± 0.000	0.000 ± 0.000	0.007 ± 0.009	0.000 ± 0.000	0.000 ± 0.000
survive	0.045 ± 0.015	0.044 ± 0.014	0.056 ± 0.016	0.046 ± 0.015	0.053 ± 0.016
gather	0.020 ± 0.010	0.021 ± 0.012	0.012 ± 0.007	0.007 ± 0.005	0.009 ± 0.004
overall	0.200 ± 0.013	0.199 ± 0.012	0.186 ± 0.012	0.140 ± 0.011	0.162 ± 0.010

Table 3: Mean human normalized score for all Avalon tasks for PPO, HELMv2, and SHELIM after 50M interaction steps. We show mean and standard deviations.

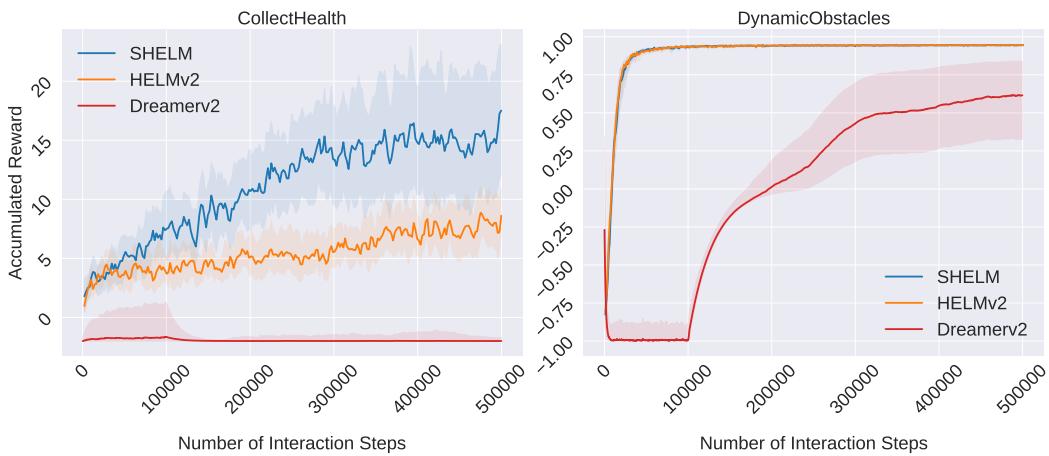


Figure 14: IQM and 95% CIs across 30 seeds on CollectHealth from MiniWorld (**left**), and on DynamicObstacles from MiniGrid (**right**). Both environments exhibit randomness in form of either randomly sampled medipack, or randomly moving obstacles.