MEMORY GYM: PARTIALLY OBSERVABLE CHALLENGES TO MEMORY-BASED AGENTS

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Paper under double-blind review

ABSTRACT

Memory Gym is a novel benchmark for challenging Deep Reinforcement Learning agents to memorize events across long sequences, be robust to noise, and generalize. It consists of the partially observable 2D environments Mortar Mayhem, Mystery Path, and Searing Spotlights. These environments are believed to be unsolvable by memory-less agents because they feature strong dependencies on memory and frequent agent-memory interactions. Several commonly used related environments do not share those qualities. Empirical results based on Proximal Policy Optimization (PPO) and Gated Recurrent Unit (GRU) underline the strong memory dependency of the contributed environments. The hardness of these environments can be smoothly scaled, while different levels of difficulty (some of them unsolved yet) emerge for Mortar Mayhem and Mystery Path. Surprisingly, Searing Spotlights poses a tremendous challenge to GRU-PPO, which remains an open puzzle. Even though the randomly moving spotlights reveal parts of the environment's ground truth, environmental ablations hint that these pose a severe perturbation to agents that leverage recurrent model architectures as their memory.

1 INTRODUCTION

Memory is a vital mechanism of intelligent living beings to make favorable decisions sequentially under imperfect information and uncertainty. One's immediate sensory perception may not suffice if information from past events cannot be recalled. Reasoning, imagination, planning, and learning are skills that may become unattainable. When developing autonomously learning decision-making agents, adding memory mechanisms as a recurrent neural network (Werbos, 1990) or a transformer (Vaswani et al., 2017) led to successfully learned policies in both virtual and real-world tasks. For instance, Deep Reinforcement Learning (DRL) approaches master complex video games such as Capture the flag (Jaderberg et al., 2018), StarCraft II (Vinyals et al., 2019), and DotA 2 (Berner et al., 2019). Examples of successes in real-world problems are dexterous in-hand manipulation (Andrychowicz et al., 2020) and controlling tokamak plasmas (Degrave et al., 2022). In addition to leveraging memory, these tasks require vast amounts of computation resources and additional methods (e.g. domain randomization, incorporating domain knowledge, ect.), which make them undesirable for solely benchmarking an agent's ability to interact with its memory meaningfully.

We propose Memory Gym as a novel and open source[1] benchmark consisting of three unique environments: Mortar Mayhem, Mystery Path, and Searing Spotlights. These environments challenge memory-based agents to memorize events across long sequences, generalize, be robust to noise, and be sample efficient. By accomplishing the desiderata that we define in this work, we believe that Memory Gym has the potential to accelerate the development of DRL agents leveraging memory. All three environments are not solvable without memory. This allows users to assure early on whether their developed memory mechanism is working or not. To fit the problem of sequential decision making, agents have to frequently leverage their memory to solve the posed tasks by Memory Gym. Several related environments ask the agent only to memorize initial cues, which require infrequent agent-memory interactions. Our environments are smoothly configurable. This is useful to adapt the environment's difficulty to the available resources, while easier difficulties can be used as a proof of concept. Competent methods can show off themselves in new challenges or identify their limits in a profound way. All environments are procedurally generated to evaluate the agent's

[1] Dear reviewers, please find the zip archive attached as supplementary file (entire codebase and videos).

ability to generalize to unseen levels (or seeds). Due to the aforementioned configurable difficulties, the trained agent can be evaluated on out-of-distribution levels. Memory Gym's significant dependencies are gym (Brockman et al., 2016) and PyGame[2]. This allows Memory Gym to be easily set up and executed on Linux, macOS, and Windows. Multiple thousands of agent-environment interactions per second are simulated by all environments.

This paper proceeds as follows. We first define the memory benchmarks' criteria and portray the related benchmarks' landscape. Next, Mortar Mayhem, Mystery Path, and Searing Spotlights are detailed. Afterward, we show that memory is crucial in our environments by conducting empirical experiments using a recurrent implementation (GRU-PPO) of Proximal Policy Optimization (PPO) (Schulman et al., 2017) and HELM (Paischer et al., 2022). When scaling the hardness in Mortar Mayhem and Mystery Path, a full range of difficulty levels emerge. Searing Spotlights remains unsolved because the recurrent agent is volatile to perturbations of the environment's core mechanic: the randomly wandering spotlights. This observation is also apparent when training on a single Procgen BossFight (Cobbe et al., 2020) level under the same spotlight perturbations as in Searing Spotlights. At last, this work concludes and enumerates future work.

2 Comparison of Related Memory Benchmarks

2.1 Desiderata of Memory Benchmarks

Before detailing related benchmarks, we define the aforementioned desiderata that we believe are essential to memory benchmarks and benchmarks in general.

Accessibility refers to the competence to easily set up and execute the environment. Benchmarks shall be publicly available, acceptably documented, and open source while running on the commonly used operating systems Linux, macOS, and Windows. Linux, in general, is important because many high-performance computing (HPC) facilities employ this operating system. As HPC facilities might not support virtualization, benchmarks should not be solely deployed as a docker image or similar. At last, benchmarks shall run headless because otherwise, these potentially rely on dependencies like xvfb or EGL, which HPC facilities may not support as well. Suppose relevant benchmark details, such as environment dynamics, are missing. In that case, it can be desirable to support humanly playable environments so that these can be explored in advance.

Fast simulation speeds, which achieve thousands of steps per second (i.e. FPS), allow training runs to be more wall time efficient, enabling to upscale experiments and their repetitions or faster development iterations. The benchmark's speed also depends on the time it takes to reset the environment to set up a new episode for the agent to play. Towards maxing out FPS on a single machine, benchmarks shall be able to run multiple instances of their environments concurrently.

High diversity attributes environments that offer a large distribution of procedurally generated levels to reasonably challenge an agent's ability to generalize (Cobbe et al., 2020). In addition, it is desirable to allow the environment to be smoothly configurable to evaluate the agent at out-of-distribution levels.

Scalable difficulty is a property that shall make environments controllable such that their current hardness can be increased or decreased. Configuring an environment to be easier can have benefits: a proof-of-concept state is sooner reachable while developing novel methods, and research groups can fit the difficulty to their available resources. Moreover, increasing the difficulty ensures that already competent methods may prove themselves in new challenges to demonstrate their abilities or limits.

Strong dependency on memory refers to tasks that are only solvable if the agent can recall past information (i.e. successfully leveraging its memory). Section 2.4 describes partially observable environments that can be solved to some extent without memory. While memory-based agents might more efficiently solve these tasks, these do not guarantee that the agent's memory is working. To ensure that the utilized memory mechanism is working and does not suffer from bugs, this criterion cannot be omitted by benchmarks targeting specifically the agent's memory.

[2] `https://www.pygame.org`

Table 1: An overview of the simulation speed and meta desiderata of the considered environments. The meta desiderata cover the criteria that are applicable to any benchmark in DRL. The mean FPS are measured across 100 episodes using constant actions. Procgen is averaged across its memory distribution environments, and so is Memory Gym. The other benchmarks are measured using a single environment. ● refers to true and ○ to false. Appendix B provides further details.

Benchmark	Mean FPS	Meta Desiderata										
		Publicly Available	Open Source	Linux	macOS	Windows	Headless	Docker	Concurrent	Playable	High Diversity	Scalable Difficulty
Memory Gym (ours)	10123	●	●	●	●	●	●	○	●	●	●	●
Procgen Memory Distribution (Cobbe et al., 2020)	18530	●	●	●	●	●	●	○	●	●	●	●
DM Ballet (Lampinen et al., 2021)	6631	●	●	●	●	●	●	○	●	●	●	●
MiniGrid Memory (Chevalier-Boisvert et al., 2018)	5185	●	●	●	●	●	●	○	●	●	○	●
VizDoom (Wydmuch et al., 2018)	549	●	●	●	●	●	●	○	●	●	●	●
DM Memory Task Suite (Fortunato et al., 2019)	442	●	○	●	●	●	○	●	●	●	●	●
DM Lab 30 (Beattie et al., 2016)	433	●	●	●	○	○	○	○	●	●	●	●
DM Numpad (Parisotto et al., 2020)		○										
DM Memory Maze (Parisotto et al., 2020)		○										
DM Object Permanence (Lampinen et al., 2021)		○										

Strong dependency on frequent memory interactions is a property of tasks that forces the agent to recall information from and add information to its memory frequently. We believe this is more suitable for sequential decision-making problems because some related environments can be turned into supervised learning problems (2.5) and therefore only assess the memory's capacity and potentially its robustness to noise.

2.2 Considered Environments

A diverse set of environments were used in the past to challenge memory-based agents. Some of them are originally fully observable but are turned into partially observable Markov Decision Processes (POMDP) by adding noise or masking out information from the agent's observation space. For instance, this was done for the Arcade Learning Environment (Bellemare et al., 2013) by using flickering frames (Hausknecht & Stone, 2015) and common control tasks by removing the velocity from the agent's observation (Heess et al., 2015; Meng et al., 2021; Shang et al., 2021). These environments do not require the agent to memorize long sequences and can already be approached using frame stacking. Control tasks also touch on the context of Meta Reinforcement Learning (Meta RL), where memory mechanisms are prominent (Wang et al., 2021; Melo, 2022; Ni et al., 2022). The same applies to Multi-Agent Reinforcement Learning (Berner et al., 2019; Baker et al., 2020; Vinyals et al., 2019). As we solely focus on benchmarking the agent's memory and its ability to generalize, we do not compare Memory Gym to environments of more complex contexts such as DM Alchemy (Wang et al., 2021), Crafter (Hafner, 2021), or Obstacle Tower Juliani et al. (2019). Those might need additional components to the agent's architecture and its training paradigm. Within this section, we consider benchmarks (Table 1) that were used by the recently contributed memory approaches MRA (Fortunato et al., 2019), GTrXL (Parisotto et al., 2020), HCAM (Lampinen et al., 2021), HELM (Paischer et al., 2022), and A2C-Transformer (Sopov & Makarov, 2022). By examining these works, it becomes apparent that all of them use different environments to evaluate their methods, making their results harder to compare.

2.3 Meta Desiderata

Table 1 provides information on the meta desiderata of the considered environments. Some environments are inaccessible to some extent, as some cannot be run headless. DM Memory Maze (Parisotto et al., 2020), DM Numpad (Humplik et al., 2019), and DM Object Permanence (Lampinen et al., 2021) are not publicly available and can, therefore, not be used to reproduce and compare results in adjacent research. DM Memory Task Suite (Fortunato et al., 2019) is not open source and can only

be accessed via docker. It may be for these reasons that DM Memory Task Suite, Object Permanence, Memory Maze, and Numpad are not widely used yet. In contrast to this, DM Lab 30 (Beattie et al., 2016) has more uses, but the available environments, especially those used in the context of memory, are superficially documented. Parisotto et al. 2020 divide these environments into reactive and memory tasks without further reasoning. Potential users have to explore these environments by playing them, which is possible on machines running Linux only. Procgen (Cobbe et al., 2020), DM Ballet (Lampinen et al., 2021), MiniGrid (Chevalier-Boisvert et al., 2018), and Memory Gym (ours) are the only environments that achieve a throughput of thousands of steps per second. 3D environments usually achieve a smaller throughput, like VizDoom (Wydmuch et al., 2018) or DM Memory Task Suite (Fortunato et al., 2019).

2.4 Strong Dependency on Memory

As stated before, if an environment is solvable to some extent using an agent without memory, it is not easy to differentiate whether the memory mechanism is working. This impression can be retrieved by examining the results of Sopov & Makarov 2022 on the VizDoom environments where a policy without memory makes progress or achieves comparable performances. The six environments of Procgen's memory distribution leave us with controversial thoughts. Paischer et al. 2022 show results in these environments that indicate that a memory-less approach can perform similarly to a memory one. We further take a closer look at Miner. The agent can momentarily perceive some cues related to past steps of the episode: its last action is retrievable from its rotation. At the same time, the density of vanished tiles shows the agent whether this region was explored or not. Exploiting these cues potentially helps memory-less agents to find successful strategies and make us believe that this environment does not strongly depend on memory, while doubtlessly, a memory-based agent should be more efficient concerning the number of steps needed to solve the entire task. Another problem is that the mean cumulative reward is usually reported, which averages the rewards achieved by collecting diamonds and using the exit. This data does not precisely tell how good an agent is at completing the entire task. Especially recalling the exit's position seems crucial to succeeding as soon as possible. Reporting the success rate and the episode length should provide more meaningful insights. The environments Heist and Maze can be of strong dependence on memory, but only if tiny levels, which memory-less agents trivially solve, are excluded.

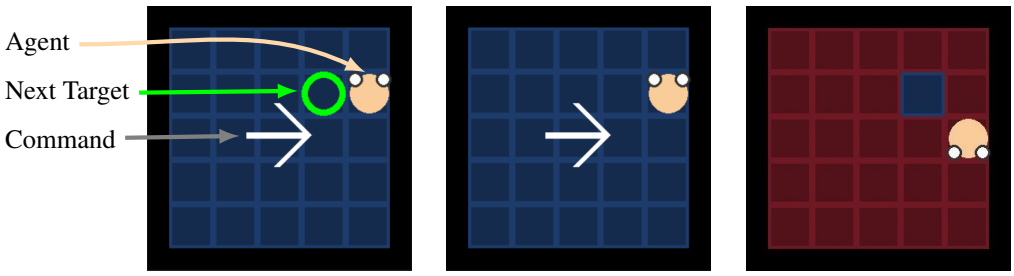
2.5 Strong Dependency on Frequent Memory Interactions

Concerning frequent memory interactions, we believe that MiniGrid Memory (Chevalier-Boisvert et al., 2018), Spot the Difference (Fortunato et al., 2019), and DM Ballet (Lampinen et al., 2021) are not well suited to the need for memory in sequential decision making. These environments demand the agent's memory to solely memorize the to-be-observed goal cues during the very beginning of the episode. Once this cue is memorized, there is no need to manipulate the agent's memory further. Simply maintaining it is enough to solve the task. It can be hypothesized that the extracted features from observing the goal cues are sufficient to solve the ballet environment. To show this, the ballet environment can be made fully observable (markovization) by feeding the entire sequence of cues to a recurrent encoder that extracts features that are utilized by the agent's policy. Consequently, the policy does not need to maintain its memory in this case. The task at hand gets much easier because the agent does not need to make obsolete decisions while observing the sequence of cues as its position is frozen. These tasks would, therefore, only challenge the capacity and robustness to noise of the agent's memory. We believe this can be done more efficiently by other disciplines, for example, supervised learning.

3 Memory Gym Environments

Mini-games of the commercial video game Pummel Party[3] inspired Memory Gym's environments. The agent perceives all environments using 84×84 RGB pixels, while its action space is multi-discrete, featuring two dimensions of size three. One dimension allows the agent to move horizontally (no movement, move left, move right), and the other concerns the agent's vertical locomotion (no movement, move up, move down). Mortar Mayhem and Mystery Path also feature variants

[3] http://rebuiltgames.com/



(a) Annotated Ground Truth (b) Agent Observation (c) Visual Feedback

Figure 1: Mortar Mayhem's relevant entities are presented by the annotated ground truth of the environment (a). The green circle, which is solely part of the ground truth, indicates the very next tile to move to. Once the agent has solved this command, the green circle moves to the next target tile. At the start of an episode, the commands are rendered sequentially onto the agent's observation (b) while the agent cannot move. Once all commands are shown, the agent has to move to the target tile in a certain amount of time. As soon as the time for executing the current command is over, the agent's success is verified, as seen in figure (c). This visual feedback is perceivable by the agent. After a delay of a few steps, the agent can approach the following command if the episode did not terminate yet due to failure or completing the entire command sequence.

based on grid-like locomotion. This way, the action space is discrete and allows the agent to not move at all, rotate left, rotate right, or move forward. Subsequently, we further detail the environments' dynamics, their peculiarities towards memory, and how these can be smoothly scaled to support varying difficulty levels. All parameters used for scaling the environments' hardness and their default values are found in appendix C.4. Appendices C.1 to C.3 visualize played episodes.

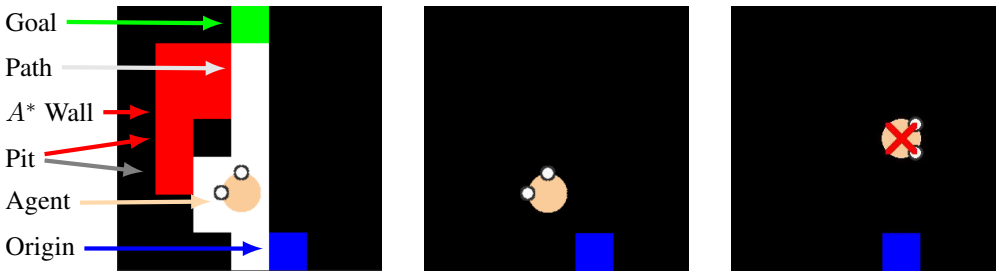
3.1 Mortar Mayhem

Mortar Mayhem (MM) (Figure 1) takes place inside a grid-like arena and consists of two tasks that strongly rely on memory. At first, while unable to move, the agent has to memorize a sequence of five commands (Clue Task), and afterward, it has to execute each command in the observed order (Act Task). One command orders the agent to move to one adjacent floor tile or to stay at the current one. If the agent fails, the episode terminates while receiving no reward. Upon successfully executing one command, the agent receives a reward of $+0.1$. MM can be reduced to provide only the Act Task (MMAct). In this case, the command sequence is fully observable as a one-hot encoded feature vector. The Act Task requires an agent to leverage its memory frequently because otherwise, the agent is left in uncertainty. It does not know which commands were already executed to fulfill the next one, while there are nine tiles at maximum to consider. A successful episode of MM with a command sequence of five commands lasts for 138 steps, while MMAct only takes 119 steps due to leaving out the clue task.

The hardness of MM can be further simplified by equipping the agent with a grid-like movement (MMGrid, MMActGrid). The agent is now capable of moving one tile at a time. Before, it needed at least four to five steps to overcome the same distance. Because of the grid-like movement, the agent is not asked to move to diagonal tiles. To ensure a meaningful task, the agent must execute ten commands, not five. Now, successful episodes take 117 steps in MMGrid and 78 in MMActGrid. Examples to raise MM's difficulty are to extend or sample the number of commands or the delay between command execution.

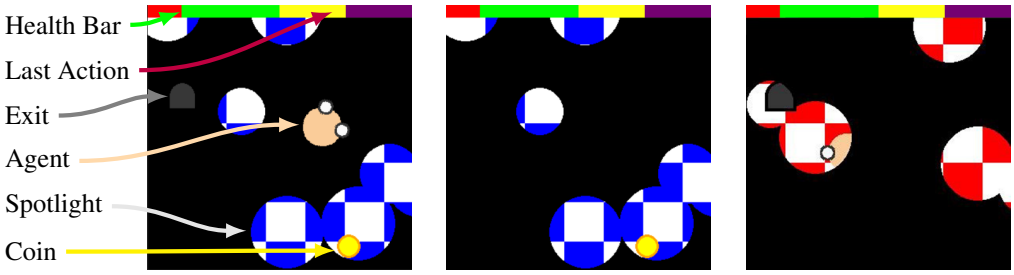
3.2 Mystery Path

Mystery Path (MP) (Figure 2) challenges the agent to traverse an invisible path in a grid-like level of dimension 7×7, while only the path's origin is visible to the agent. If the agent moves off the path (i.e. falls down the pit), the agent is relocated to its origin. The episode terminates if the agent reaches the goal or runs out of time (512 steps). Upon reaching the goal, the environment signals a reward of $+1$. To overcome uncertainty in this environment, the agent has to memorize several



(a) Annotated Ground Truth (b) Agent Observation (c) Visual Feedback

Figure 2: Mystery Path's relevant entities are described by the environment's annotated ground truth (a). The walkable parts of the path are colored blue (origin), green (goal), and white (path). Every other part of the environment is considered a pit (black and red) where the agent falls off and is then relocated to the path's origin during its next step. The initially randomly chosen red tiles (A^* Walls) are not considered during path generation. The agent observes itself and the path's origin (b). If the agent is off the path, a red cross provides visual feedback (c), which is also observed.



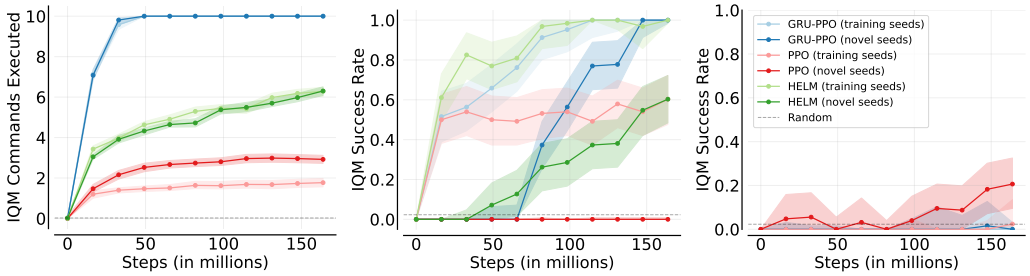
(a) Annotated Ground Truth (b) Agent Observation (c) Visual Feedback

Figure 3: All relevant entities can be identified in the annotated ground truth of Searing Spotlights (a). The top rows of pixels feature the agent's remaining health points and its last action that two chunks and three colors encode. Yellow circles correspond to coins, while the somewhat rounded gray shape resembles the exit. If the exit is open (i.e. no coins are left), it turns green. The floor of the environment is a chessboard colored blue and white. As seen in the agent's observation (b), the spotlights hide or reveal the other entities. As additional visual feedback (c), the blue floor tiles turn red if a spotlight spots the agent.

locations: its steps on the path and the locations where it fell off. The invisible path is procedurally generated using the path-finding algorithm A^* (Hart et al., 1968). At first, the path's origin is sampled from the grid's border. Then, the goal is placed in a random position on the opposing side. Usually, A^* seeks to find the shortest path. A^*'s cost function is sampled to ensure that wide variety of paths is procedurally generated. The path generation randomizes some cells to be untraceable (A^* walls). Note that the walls are considered pits and not physical obstacles. MP can also be simplified to a grid variant (MPGrid) like MMGrid and MMActGrid, featuring the single discrete action space of four actions, while the agent's time limit is reduced from 512 steps to 128.

3.3 Searing Spotlights

Searing Spotlights (Figure 3) is perceived as a pitch-black surrounding by the agent where the only information is unveiled by roaming and threatening spotlights. While initially starting with a limited number of health points (e.g. 100), the agent loses one health point per step if hit by a spotlight. The episode terminates if the agent has no remaining health points or runs out of time (512 steps). Because of the posed threats, the agent has to hide in the dark. To successfully run away from closing in spotlights, the agent must memorize its past actions and at least one past position of itself to infer its current location. That also requires the agent to carefully use its health point budget to figure



(a) Mortar Mayhem Act Grid (b) Mystery Path Grid (c) Searing Spotlights

Figure 4: Training and generalization performances show strong dependence on memory.

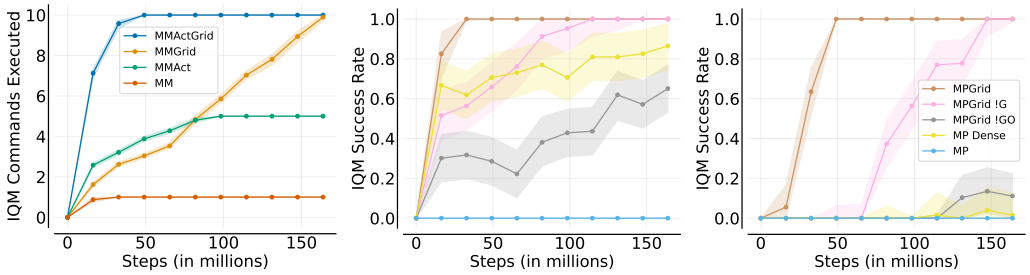
out its location - ideally once briefly. To avoid numb policies, two additional tasks are added to the environment that requires the agent to traverse the environment. The first one randomly places an exit in the environment, which the agent can use to receive a reward of $+1$ and terminate the episode. Secondly, a coin collection task is added. Before using the environment's exit, the agent has to collect a certain number of randomly positioned coins. Collecting one coin grants a reward of $+0.25$ to the agent. If the agent successfully uses its memory, it can infer its current location, and recall the locations of the exit and the coins. A simplified grid version of Searing Spotlights is not available. As a default simplification, the episode starts with perfect information, and after a few steps, the global light is dimmed until off. Appendix C.4 enumerates multiple parameters that organize the measures, behavior, and spawning frequency of the spotlights. Other parameters concern the reward function, the agent's properties, and the visual representation of Searing Spotlights.

4 Baseline Experiments

We run empirical baseline experiments using the DRL algorithm Proximal Policy Optimization (PPO) (Schulman et al., 2017). To support memory, our implementation adds a gated recurrent unit (GRU) (Cho et al., 2014) to the actor-critic model architecture of PPO (GRU-PPO). Appendix D describes the model architecture and the used hyperparameters. Related state-of-the-art memory-based approaches such as MRA (Fortunato et al., 2019), GTrXL (Parisotto et al., 2020), HCAM (Lampinen et al., 2021), and ALD (Parisotto & Salakhutdinov, 2021) are not considered, because there is no applicable code available, while these methods are expensive to reproduce. That does not account for HELM (Paischer et al., 2022), which we successfully added to our training framework. However, HELM has poor wall-time efficiency (see figs. 15 and 16 in appendix E). Due to the vast transformer component consisting of 18 blocks, the policy takes much more time to produce actions during inference. One GRU-PPO training run takes about ten hours in MMActGrid with a sequence length of 78, while HELM needs at least six times longer. This effect worsens for longer sequences. Therefore, HELM is only used in MMActGrid and MPGrid. We repeated all experiments five times. Generalization is assessed on ten novel seeds, which are repeated five times. Hence, each data point aggregates 250 episodes. The subsequent sample efficiency curves show the interquartile mean and a confidence interval of 0.95 as recommended by Agarwal et al. (2021).

4.1 Dependency on Memory

To support our claim that Memory Gym's environments strongly depend on memory, the agents are trained with PPO (memory-less), GRU-PPO, and HELM on MMActGrid, MPGrid (hidden goal), and Searing Spotlights. Figure 4(a) shows the results on MMActGrid that emphasize that the Act Task in MM depends on memory. GRU-PPO successfully executes ten commands after 50 million training steps, while memory-less PPO solves only one to two commands. HELM is inferior to GRU-PPO as it converges to about six successful commands. Concerning MPGrid (Figure 4(b)), GRU-PPO needs the entire training time to succeed and generalize. HELM has lower performance because its success rate converges to 0.6 during generalization while it has better results when evaluated on training seeds. PPO achieves a success rate of about 0.6 under high variance on training seeds while failing to generalize to novel ones. Results of Searing Spotlights are illustrated in Fig-



(a) Mortar Mayhem Novel Seeds (b) Mystery Path Training Seeds (c) Mystery Path Novel Seeds

Figure 5: By scaling the hardness of Mortar Mayhem and Mystery Path, unsolved and diverse levels of difficulties emerge. The agents are trained using GRU-PPO. MMAct and MM ask for five commands to be executed and not ten. Only the generalization performance is shown because, as in figure 4(a), both performances are nearly identical. In MPGrid, the goal and origin are visible, while the other two experiments hide the goal (!G) or both (!GO). MP Dense provides a denser reward signal. Whenever the agent touches a tile of the path for the first time, it is rewarded by 0.03.

ure 4(c). GRU-PPO and PPO are barely able to complete this environment. To further investigate this outcome, subsection 4.3 examines environment ablations and hints at why randomly moving spotlights may be a significant issue to memory based on recurrence. Because of this, we did not allocate resources to train HELM in this setting.

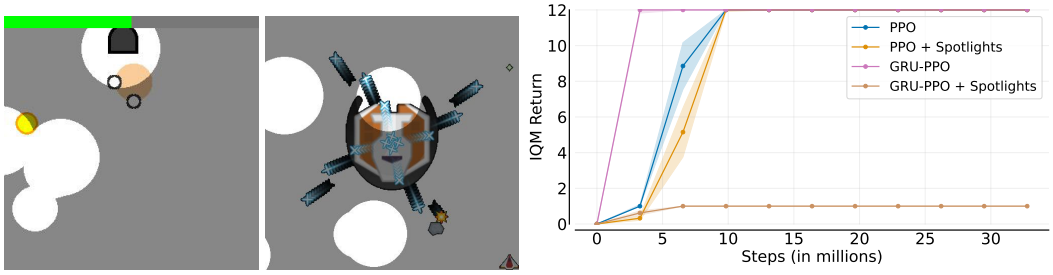
4.2 Levels of Difficulty in Mortar Mayhem and Mystery Path

Levels of difficulty, ranging from easy to unsolved, emerge when scaling Mortar Mayhem and Mystery Path and if trained using GRU-PPO. As seen in figure 5(a), MMActGrid only needs 50 million steps to accomplish the whole task, while its non-grid counterpart (MMAct) needs twice as long to solve only five commands. Note that the available commands in the grid variants comprise only five command choices and not the full range of nine ones. Adding the Clue Task notably increases the agent's challenge because the grid variant (MMGrid) needs the entire training time to succeed. At the same time, the complete task (MM) reaches a score similar to memory-less PPO on MMActGrid (Figure 4(a)). The performance on training and novel seeds is nearly identical, which can be explained by the high uncertainty of this environment. A single observation leaves the agent clueless about which of the nine tiles to move next. Therefore the agent has no other choice but to obtain the ability to memorize and recall past events. If the portrayed challenges of Mortar Mayhem do not suffice, its hardness can be further advanced by sampling the delays between showing or executing commands. This is similar to how DM Ballet samples the number of dancers and the delays between dances, which causes the recurrent agent to be ineffective (Lampinen et al., 2021).

Concerning MPGrid, if the goal and origin are part of the agent's observation, it takes 50 million steps for the agent to generalize to novel seeds, as shown in figure 5(c). Hiding the goal and origin degrades the agent's performance to a success rate of 0.2 on novel seeds. If only the goal is hidden, the agent needs the entire training time to reach a success rate of 1.0. Agents trained on MP or MP Dense are ineffective on novel seeds. During training, the agent in MP Dense makes progress due to the help of a denser reward function that signals a reward of 0.03 for visiting a tile of the path for the first time. Consequently, we also experimented with a negative reward of -0.001 for each step taken, severely hurting the training performance. To further raise MP's difficulty, it can be imagined that a maze-like path with dead ends will be a much more significant challenge. Also, scaling the dimensions of the environment is considerable. However, a larger environment may not fit into the agent's observation that an egocentric observation could compensate.

4.3 Recurrence is Vulnerable to Spotlight Perturbations

Searing Spotlights remains a puzzle to GRU-PPO. It is difficult to tell whether the agent's trained policy learned anything meaningful. Collecting the coin seems worse than chance. The agent's remaining health points drop to zero in nearly all evaluated episodes because avoiding the spotlights



(a) Fully Observable (b) Spotlight Perturbation (c) BossFight Performance on Training Seeds

Figure 6: Under perfect information, the noise inflicted by spotlight perturbations harms the recurrent agents' performance in Searing Spotlights (a) and Procgen's BossFight (b). (c) denotes the training performances on training seeds when trained with and without perturbations using PPO and GRU-PPO.

does not work well. It seems that the agent struggles to determine what it controls. Even though the spotlights unveil information on the ground truth of the environment or leave room for exploitation, the recurrent agent seems severely hurt by the perturbations inflicted by the randomly moving spotlights, which can be considered noise.

Regardless of any executed measure (see appendix F for details), for instance, environmental ablations, model architectures, and hyperparameters, progress in learning a reasonable behavior is lacking. When trained with GRU-PPO, the only solvable scenario is to remove the spotlights. In this case, if the global light is initially turned on (perfect information) and dimmed until off during the first few steps, the agent rapidly collects the coin and uses the exit. In contradiction, if the global light is slightly dimmed while spotlights are present (Figure 6(a)), GRU-PPO fails. On the other hand, memory-less PPO quickly succeeds because this fully observable task is trivial. Those results are also apparent in training a different environment. We choose Procgen's BossFight because it rather needs fewer steps to train as seen in the results of Cobbe et al. 2020. BossFight is set up to utilize only one level causing the boss always to behave the same. We extrapolate this level by 100,000 spotlight perturbation seeds under perfect information. Its background is rendered white to match Searing Spotlight's visual appearance more closely. The now-established BossFight task (Figure 6(b)) invites overfitting. Figure 6(c) shows results with and without spotlight perturbations on PPO and GRU-PPO. Notably, GRU-PPO, perturbed by spotlights, struggles.

5 Conclusion and Future Work

By accomplishing the desiderata that we have defined and examined in this work, and by evaluating the baseline experiments, we believe that Memory Gym has proven potential to benchmark Deep Reinforcement Learning agents leveraging memory. Memory Gym's unique environments, Mortar Mayhem, Mystery Path, and Searing Spotlights, strongly depend on memory and frequent agent-memory interactions. As the environments' difficulties are smoothly scalable, current and future approaches to memory may find their right fit for examination. Searing Spotlights poses a yet unsolved challenge to agents leveraging recurrent neural networks. It will be intriguing to see whether adjacent memory approaches suffer from the noisy perturbations inflicted by the spotlights. In future work, we aim to leverage Memory Gym to examine other DRL algorithms and their memory architectures, such as transformer-based episodic memory. We further plan on developing and adding more environments and extending Mystery Path by generating more complex paths with dead ends and scaling up the environment's dimension.

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A INSTALLATION AND EXECUTION OF MEMORY GYM

```
# Create Anaconda environment
$ conda create -n memory-gym python=3.7 --yes
$ conda activate memory-gym
# Install Memory Gym
$ pip install memory-gym
# Play Mortar Mayhem
$ mortar_mayhem
```

Figure 7: Install and play Memory Gym's environments.

Memory Gym is available as a PyPi package[4], which installs the required dependencies gym and PyGame. We recommend to utilize Anaconda[5] to allow for console scripts to be executed. This way, the environments can be played using the following commands:

```
$ mortar_mayhem
$ mortar_mayhem_b
$ mortar_mayhem_grid
$ mortar_mayhem_b_grid
$ mystery_path
$ mystery_path_grid
$ searing_spotlights
```

Figure 8: Console scripts to play Memory Gym's environments

```
import gym
import memory_gym

# Configure desired reset parameters
options = {"allowed_commands": 5, "command_count": [5]}

env = gym.make("MortarMayhem-v0")
obs = env.reset(options)
print(obs["visual_observation"].shape) # (84, 84, 3)
print(env.action_space)                # MultiDiscrete([3 3])

done = False
while not done:
  action = env.action_space.sample()
  obs, reward, done, info = env.step(action)
```

Figure 9: Code interactions with Memory Gym environments

[4]Dear reviewers, the package will be available upon acceptance due to anonymity.
[5]https://www.anaconda.com/products/distribution

B EXTENDED RELATED BENCHMARK OVERVIEW

Table 2: Comparison of the simulation speed of our benchmark to related ones. A constant action is executed to measure the speed. Procgen encompasses the mean steps per second for the environments CaveFlyer, Jumper, Heist, Dodgeball, Maze, and Miner. The reset duration is included in steps per second. Some benchmarks are only measured by a single environment. The measurement was done on a AMD Ryzen 7 2700X.

Benchmark	FPS		Reset Duration
	Mean	Std	Mean (seconds)
Procgen Memory Distribution (Cobbe et al. (2020))	18530	5453	4e-6
Mystery Path (ours)	12187	330	5e-4
Mortar Mayhem (ours)	11692	179	2e-4
Atari Breakout (Bellemare et al. (2013))	7117	19	6e-3
DM Ballet (Lampinen et al. (2021))	6631	795	6e-4
Searing Spotlights (ours)	5490	69	5e-4
MiniGrid Memory (Chevalier-Boisvert et al. (2018))	5185	141	1e-3
MiniWorld TMaze (Chevalier-Boisvert et al. (2018))	1162	65	6e-4
GridVerse MemoryNineRooms (Baisero & Katt (2021))	938	89	1e-3
ML-Agents Hallway (Juliani et al. (2018))	702	42	1e-3
VizDoom My Way Home (Wydmuch et al. (2018))	549	22	3e-3
Crafter (Hafner (2021))	482	33	1e-1
DM Spot the Difference (Fortunato et al. (2019))	442	20	1e-1
DM Lab 30 rooms_watermaze (Beattie et al. (2016))	433	53	5e-1
DM Alchemy (Wang et al. (2021))	308	31	2e-1
DM Hard Eight ball room_navigation_cubes (Gülçehre et al., 2020)	160	7	2e-1
AnimalAI 3 aai_c32_r5 (Crosby et al. (2020))	190	59	1e-2
Obstacle Tower (Juliani et al. (2019))	43	2	16e-1

C SUPPLEMENTARY ENVIRONMENT DETAILS

C.1 MORTAR MAYHEM GRID TRAJECTORY

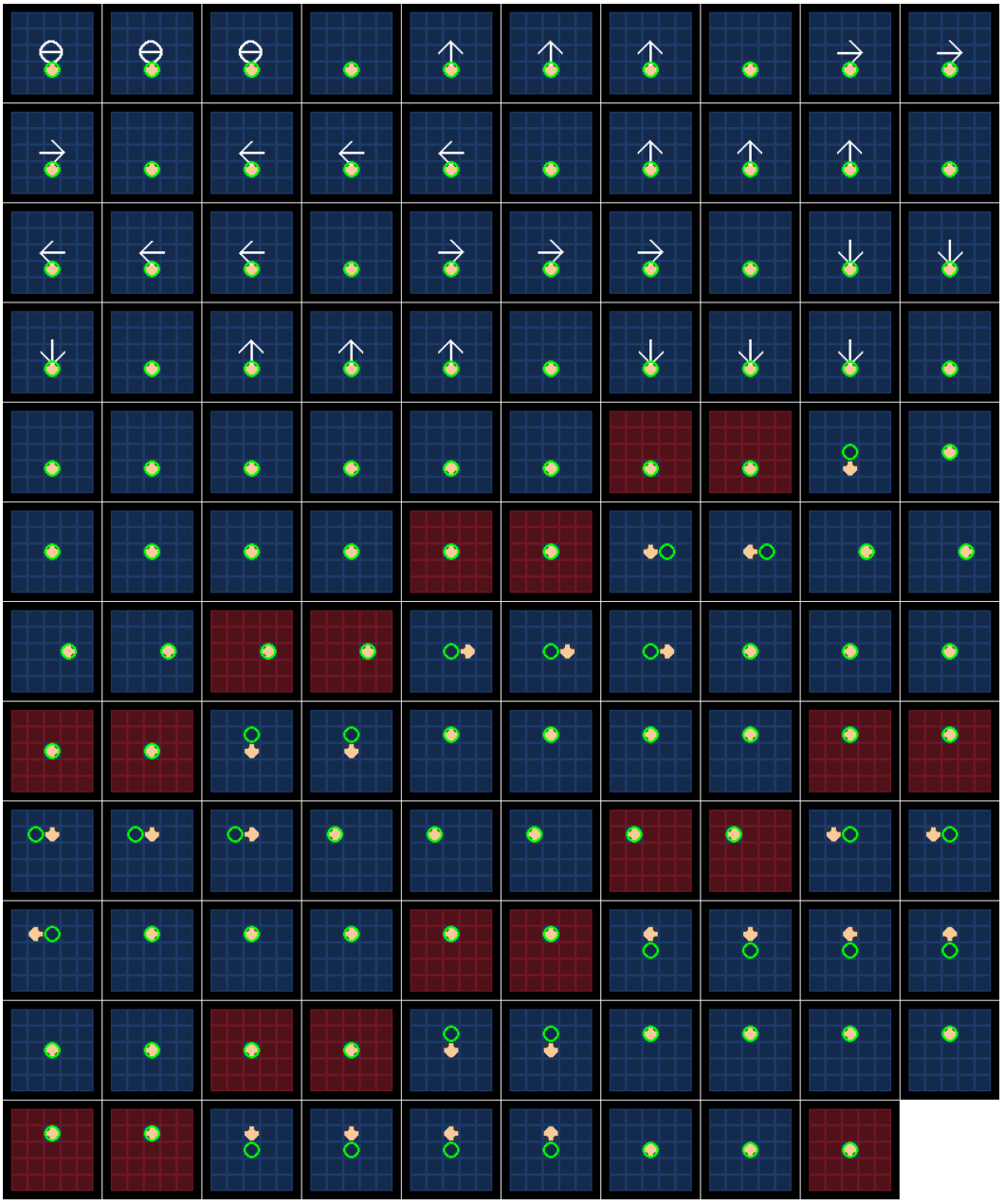


Figure 10: A successfully completed episode of Mortar Mayhem Grid showing the ground truth.

C.2 MYSTERY PATH GRID TRAJECTORY

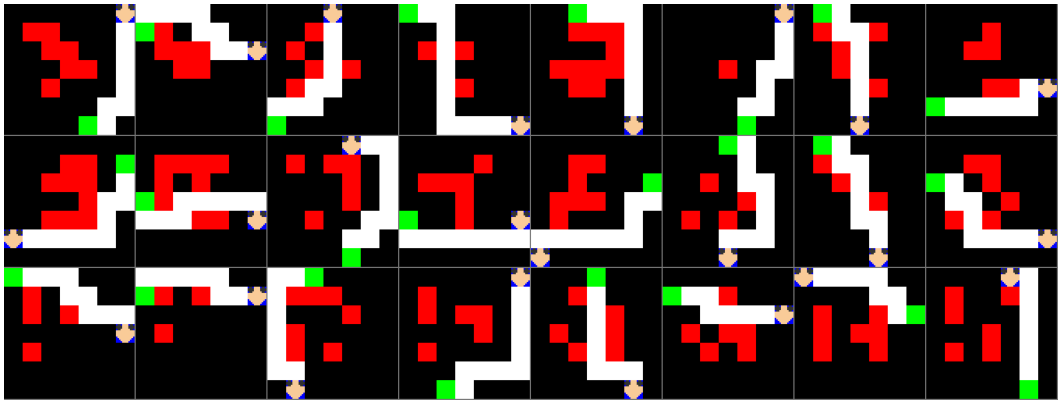


Figure 11: Various randomly generated levels in the Mystery Path environment.

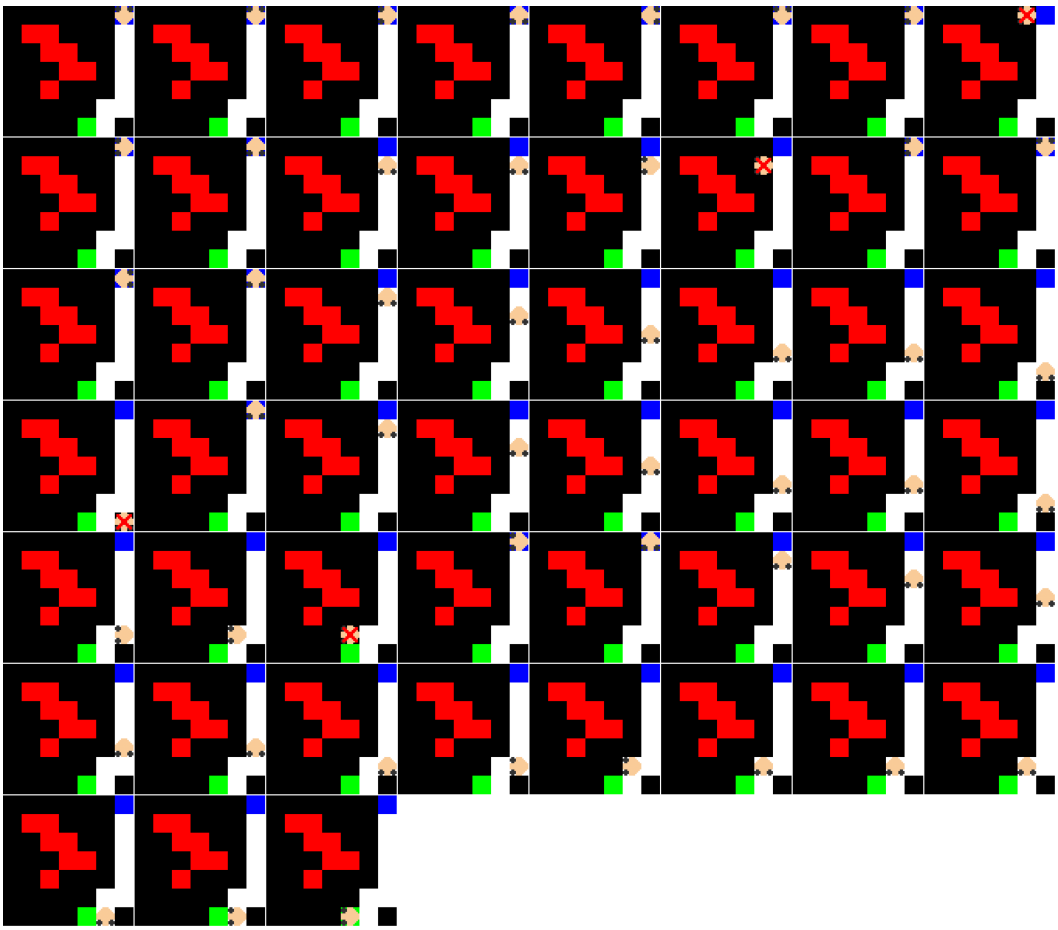


Figure 12: A successfully completed episode of Mystery Path Grid showing the ground truth.

C.3 SEARING SPOTLIGHTS TRAJECTORY

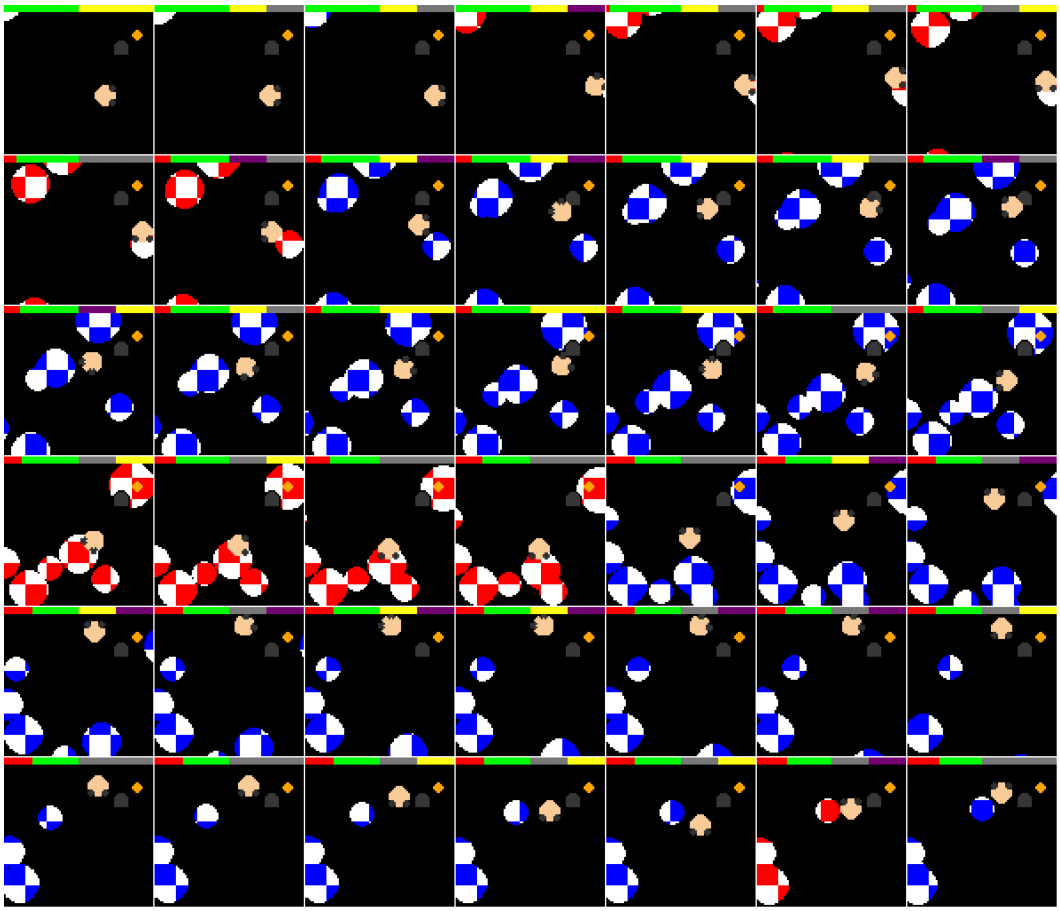


Figure 13: An excerpt of Searing Spotlights showing the ground truth and using a frame skip of four.

C.4 Reset Parameters to Configure the Environments

Table 3: These are the default parameters that we used throughout this paper as default. Parameters with a * indicate that these are uniformly sampled. Values in square brackets are discrete choices, while values in parentheses consider a range to sample from. Mortar Mayhem Grid features the same parameters as its parent, but only the modified ones are presented.

Mortar Mayhem	
Parameter	**Default**
Agent Scale	0.25
Agent Speed	2.5
Arena Size	5
Number of Available Commands	9
Number of Commands*	[5]
Command Show Duration*	[3]
Command Show Delay*	[1]
Execution Duration*	[6]
Execution Delay*	[18]
Hide Visual Feedback	False
Reward Command Failure	0
Reward Command Success	0.1
Reward Episode Success	0

Mortar Mayhem Grid	
Parameter	**Default**
Number of Available Commands	5
Number of Commands*	[10]
Execution Duration*	[2]
Execution Delay*	[5]

Mystery Path	
Parameter	**Default**
Max Episode Length	512
Agent Scale	0.25
Agent Speed	2.5
Cardinal Origin Choice*	[0, 1, 2, 3]
Hide Origin	False
Hide Goal	True
Hide Visual Feedback	False
Reward Goal	1
Reward Fall Off	0
Reward Path Progress	0
Reward Step	0

Searing Spotlights	
Parameter	**Default**
Max Episode Length	512
Agent Scale	0.25
Agent Speed	2.5
Agent Visible	False
Agent Health	100
Sample Agent Position	True
Use Exit	True
Exit Scale	0.5
Exit Visible	False
Number of Coins*	[1]
Number of Initial Spotlight Spawns	4
Number of Spotlight Spawns	30
Spotlight Spawn Interval	30
Spotlight Spawn Decay	0.95
Spotlight Spawn Threshold	10
Spotlight Radius*	(7.5-13.75)
Spotlight Speed*	(0.0025-0.0075)
Spotlight Damage	1
Light Dim Off Duration	6
Light Threshold	255
Hide Visual Feedback	False
Render Background Black	False
Reward Inside Spotlight	0
Reward Outside Spotlights	0
Reward Death	0
Reward Exit	1
Reward Coin	0.25
Reward Max Steps	0

D CHOICE OF HYPERPARAMETERS AND MODEL ARCHITECTURE

Table 4: These are the hyperparameters that we used for all training runs. The sequence length is dynamically set by the longest episode inside the batch of the gathered training data. The experiments on Searing Spotlights and Mystery Path utilized a fixed sequence length of 128. The learning rate and the entropy coefficient decay linearly.

Hyperparameter	**Value**
Training Seeds	100000
Sequence Length	Max
Number of Workers	32
Worker Steps	512
Batch Size	16384
Number of Mini Batches	8
Mini Batch Size	2048
PPO Updates	10000
Training Steps	163840000
Discount Factor Gamma	0.99
GAE Lamda	0.95
Epochs	3
Value Loss Coefficient	0.25
Max Gradient Norm	0.5
Clip Range Epsilon	0.2
Initial Learning Rate	3e-4
Final Learning Rate	1e-4
Initial Entropy Coefficient	1e-4
Final Entropy Coefficient	1e-5
HELM Beta	1000

Table 4 enumerates the utilized hyperparameters. The agent in Searing Spotlights uses a frame skip of 2. The quite large batch size is chosen to max out the wall-time efficiency of the utilized resources. One training based on GRU-PPO utilizes almost 32GB of VRAM. Most of the hyperparameters related to memory were found by running a grid search on an early version of Mortar Mayhem Grid. Besides that we made coarse hyperparameter sweeps especially for Searing Spotlights that did not yield any benefit. We tried the values 50, 100, 200, and 1000 for HELM's beta hyperparameter on MMActGrid. All values ended up with a nearly identical performance. We ultimately chose 1000 because there is not much variance in individual observations in Mortar Mayhem and Mystery Path. Overall, we rather allocated our resources to scale the difficulty of Mortar Mayhem and Mystery Path, while investigating the issues of Searing Spotlights.

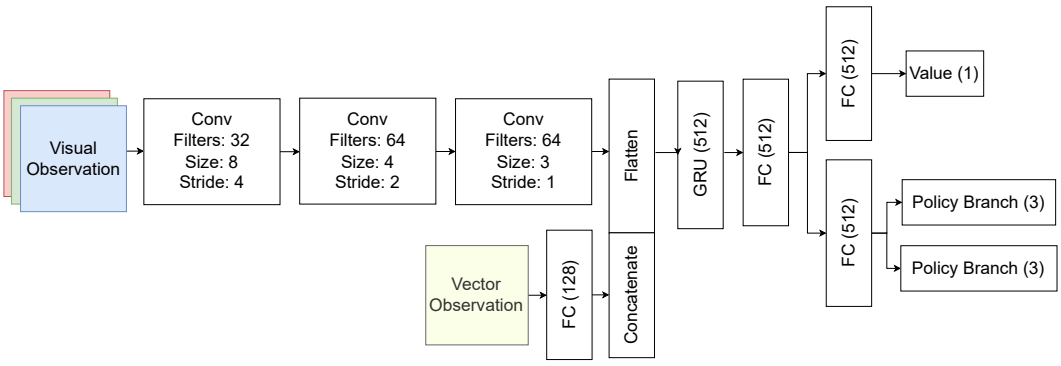


Figure 14: Actor-critic model architecture

Figure 14 illustrates the utilized model architecture for using GRU-PPO. The visual observation is processed by a commonly used convolution neural network (CNN). If a vector observation is present,

its encoded features are concatenated to the flattened features of the CNN. The concatenation is then fed into the GRU cell. After propagating a fully connected layer, the model is divided into a value and a policy stream. Before outputting their respective heads, another fully connected layer is utilized. In the case of memory-less PPO and HELM, the GRU cell is removed. If HELM is used, the model receives another encoding branch that receives the current grayscale visual observation. The observation is then propagated by a frozen hopfield and a pre-trained transformer as described by Paischer et al. 2022. The resulting features are concatenated to the ones from the CNN and the vector observation encoder.

E WALL-TIME EFFICIENCY OF HELM

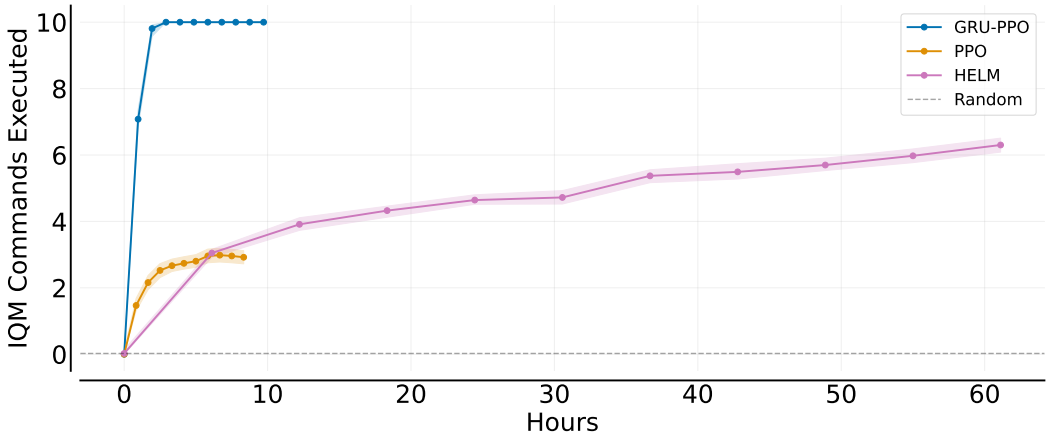


Figure 15: Generalization performances on novel seeds in Mortar Mayhem Act Grid showing the wall-time efficiency of PPO, GRU-PPO, and HELM. These experiments are run on an NVIDIA A100 Tensor-Core-GPU and an AMD EPYC 7542 CPU (32 cores).

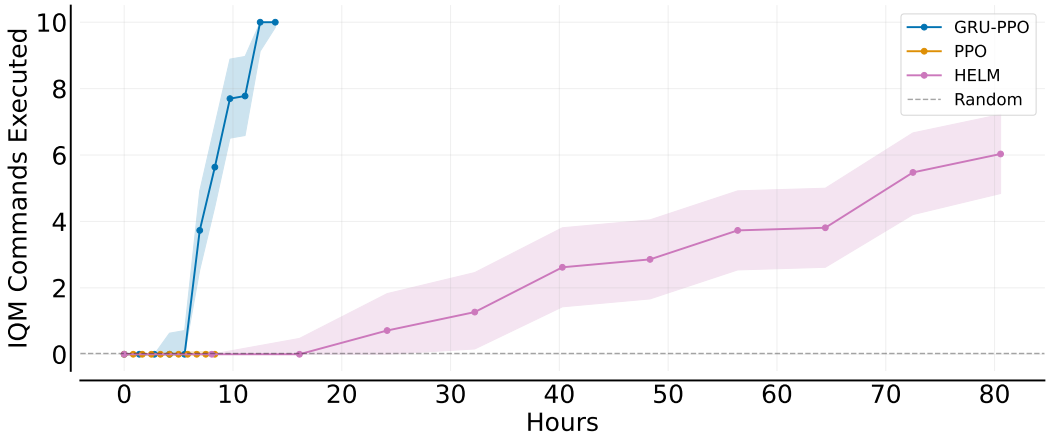
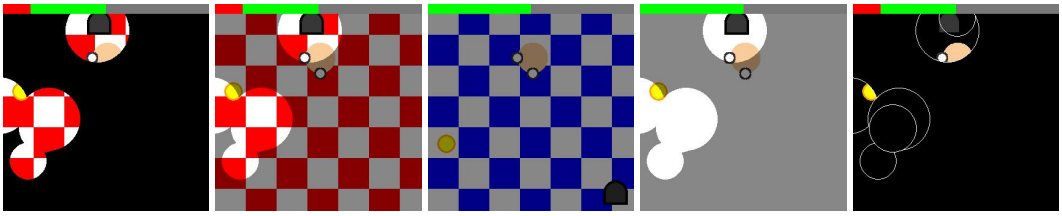


Figure 16: Generalization performances on novel seeds in Mystery Path Grid (hidden goal) showing the wall-time efficiency of PPO, GRU-PPO, and HELM. These experiments are run on an NVIDIA A100 Tensor-Core-GPU and an AMD EPYC 7542 CPU (32 cores).

F MEASURES TAKEN ON SEARING SPOTLIGHTS



(a) Default (b) Fully Observable (c) No Spotlights (d) No Chessboard (e) Black Floor

Figure 17: Varying visual representations of Searing Spotlights are examined. (a) poses the original task. (b) provides perfect information, because the global light is just dimmed. (c) disables the spotlight dynamics while dimming the global light until off. (d) removes the tiled background. (e) renders the floor black that requires to render the spotlights' circumference white.

Multiple experiments were conducted to ablate the environment's difficulty and to vary the model architecture. Figure 17 shows a few variations of the visual representation of Searing Spotlights. Whenever spotlights are present, the recurrent agent fails. Subsequently, we enumerate the measures that we tried with limited success to help the agent to learn a more meaningful policy. Increasing the scale of all entities but the spotlights or reducing the number of spotlights may have undesirable consequences to the task's quality. Random policies may be more successful under these measures.

- **Reduce episode length to ease exploration**
  - Leverage frame skipping
  - Raise agent speed
  - Scale up all entities except spotlights
- **Vary spotlights**
  - Add negative reward of -0.01 for the agent being inside the spotlights
  - Stationary spotlights
  - Fewer spotlights
  - Constant spotlight size and speed
- **Vary task**
  - Use only one coin and no exit
  - Use the exit but no coin
  - Agent always starts at the center of the level
  - Increase agent health points
  - Add negative death reward of -0.1
- **Vary agent observation**
  - Environment is fully observable for few steps
  - Make the agent, coin, exit, or all of them permanently visible
  - Add health points bar
  - Render the agent's last action onto to the observation instead of feeding a one-hot encoded feature vector
  - Feed the agent its exact position as normalized scalars
  - Slightly dim the light (perfect information)
  - Render the environment's floor black while drawing the spotlights' circumference white
- **Vary model architecture**
  - Add residual connection arounf the GRU cell
  - Use LSTM instead of GRU
  - Reduce sequence length from 128 to 64
  - Use Impala CNN Espeholt et al. (2018) instead of Nature CNN Mnih et al. (2015)
  - Add fully connected layer between CNN and GRU