Tangled Program Graphs with Indexed Memory in Control Tasks with Short Time Dependencies

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Abstract: This paper addresses the challenges of shared temporal memory for evolutionary reinforcement learning agents in partially observable control tasks with short time dependencies. Tangled Program Graphs (TPG) is a genetic programming framework which has been widely studied in memory intensive tasks from video games, time series forecasting, and predictive control domains. In this study, we aim to improve external indexed memory usage in TPG by minimizing the impact of destructive agents during cultural transmission. We test various memory resetting strategies—per agent, per episode, and a no-memory control group—and evaluate their effectiveness in mitigating destructive effects while maintaining performance. Results from Acrobot, Pendulum, and CartPole tasks show that resetting memory more often can significantly boost TPG performance while preserving computational efficiency. These findings highlight the importance of memory management in Reinforcement Learning (RL) and suggest opportunities for further optimization for more complex visual RL environments, including adaptive memory resetting and evolved probabilistic memory operations.

1 INTRODUCTION

Reinforcement Learning (RL) agents learn through trial-and-error interaction with their environment (Sutton and Barto, 2018). Deep Reinforcement Learning (DRL), with its capacity to decompose sensor inputs and build hierarchical representations of sensor data, has significantly expanded the capabilities of autonomous agents operating within complex environments (Mnih et al., 2015). Despite these advancements, DRL agents often encounter formidable obstacles in tasks necessitating robust memory functionalities (Pleines et al., 2023). This paper investigates these challenges and proposes simple strategies to enhance temporal memory capabilities in the recently-proposed genetic programming framework known as Tangled Program Graphs (TPG) (Kelly and Heywood, 2018).

Effective memory management is crucial for ensuring that agents can retain and utilize relevant information over time, particularly in environments that are only partially observable or which require long term planning. We explore various strategies for enhancing the efficiency of indexed memory in TPG, with the goal of minimizing the negative impact of destructive agents and improving overall system performance. Through a series of experiments, we evaluate different memory management approaches, including probabilistic methods for writing into memory shared among a population of agents, and investigate their impact on the performance of TPG agents in partially observable benchmark RL environments with short time dependencies. This study focuses on comparing memory management strategies within TPG, using the original version of PyTPG (Amaral, 2019) as the baseline. Our results demonstrate that clearing shared temporal memory before each evaluation episode improves agent performance by reducing the negative impact of destructive agents and lowering decision-making complexity.

2 BACKGROUND

Genetic Programming (GP) is an Evolutionary Computation paradigm that evolves computer programs using evolutionary algorithms (Brameier and Banzhaf, 2007). RL agents evolved with GP can model their environment over time through the use of temporal memory. In Linear Genetic Programming

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(LGP) (Brameier and Banzhaf, 2007), programs are represented a sequence of instructions which read and write from memory registers. LGP supports a simple form of recursive temporal memory simply by allowing registers to maintain state between sequential program executions. More generally, GP can support *indexed memory* by augmenting agents with a linear memory array and adding specialized read and write operations to the GP function set (Teller, 1994). If indexed memory is shared among agents in a population, it can also support the transmission of information between individuals by non-genetic means. Spector's (Spector and Luke, 1996b), "Culture" allows all individuals to share the same memory, similar to societal interactions, where each individual is affected by others in a shared environment, but risks "pollution" of the memory matrix by agents that perform badly.

In Visual RL, observable states are high-dimensional matrices such as video frames. TPG can directly process high-dimensional video inputs and has been tested in various gaming scenarios, outperforming traditional deep neural network RL methods in multi-task learning (Kelly and Heywood, 2018). These TPG agents were also more computationally efficient, requiring fewer calculations per action than other approaches. Their efficiency is primarily due to: 1) the hierarchical complexity of each entity evolving based on its interaction with the problem domain, unlike the fixed complexity in conventional Deep Learning (Mnih et al., 2015); and 2) within a TPG entity, subsystems often focus on different segments of the visual input, meaning only certain components are active at any specific moment (Kelly et al., 2020).

Despite visual RL providing high-resolution input, individual frames often lack the complete information required to select the best action. This *partial observability* significantly limits the agent's perception of the environment and implies that temporal memory must be available for the agent to build a mental model of its environment. TPG has successfully used emergent modularity combined with register memory *and* indexed memory to evolve problem solvers for memory-intensive tasks (Kelly et al., 2021). In short, TPG agents are composed of teams of linear genetic programs which share a single memory data structure and cooperatively manage a model of the environment which enables operation in partially observable RL tasks. In this work, we aim to enhance the effectiveness of indexed memory usage by minimizing the effects of destructive individuals during the cultural transmission of information through shared memory, advancing our understanding of the "culture" of digital organisms.

3 METHODOLOGY

3.1 Environments

The environments used in this work are partially-observable versions of the widely-studied RL benchmarks Acrobot, Pendulum, and Cartpole (Sutton and Barto, 2018), Figure 1. These tasks are selected for their high level of challenge, extensive comparative results available in the literature, and computational simplicity resulting in fast experiments.

3.1.1 Acrobot

The Acrobot task is a dynamical system involving a double pendulum with 6 observation variables, indicated in Table 1, and 500 time steps. The control task involves swinging up the lower link of the double pendulum to reach a specified target height. As shown in Figure 1, the state of the Acrobot at every time step is given by the cosine and sine of the angles of the two links in radians (θ_1, θ_2) and their angular velocities. The action space is discrete and consists of three actions: applying +1 torque, -1 torque, or no torque (0) to the second joint.

Table 1: Acrobot observation space.

Num	Observation	Min	Max
0	$Cos(\theta_1)$	-1	1
1	$Sin(\theta_1)$	-1	1
2	$Cos(\theta_2)$	-1	1
3	$Sin(\theta_2)$	-1	1
4	θ_1 Angular Velocity	-4π	4π
5	θ_2 Angular Velocity	-9π	9π

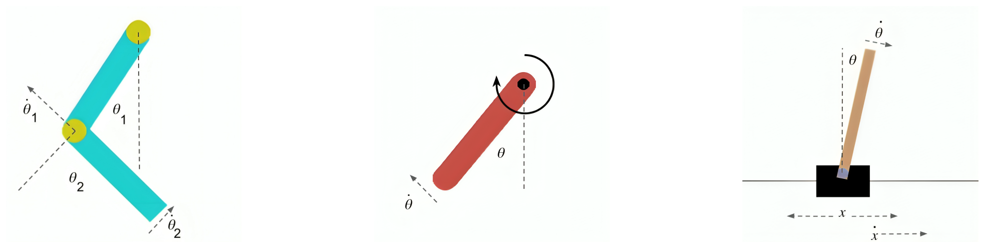
The reward function is $-t_{end}$, which is reached when the free end hits the target height ($-\cos(\theta_1) - \cos(\theta_2 + \theta_1) > 1.0$) or when the episode exceeds 500 steps. The goal is to reach the target in as few steps as possible, with each step incurring a -1 reward, and reaching the target ending with a reward of 0.

3.1.2 Pendulum Task

The Pendulum task, shown in Figure 1, is a control problem with 3 observation variables and 200 time steps. This task involves swinging up a pendulum to an upright position and keeping it balanced. The action space consists of a single continuous control variable, representing the torque applied to the joint. The observation space consists of three elements which are indicated in Table 2.

The reward function is as follows:

$$\sum_{t=1}^{t_{max}} -(\phi(\theta)^2 + 0.1 \times \dot{\theta}^2 + 0.001 \times \text{Torque}^2) \qquad (1)$$



a Acrobot. b Pendulum. c Cartpole.

Figure 1: Problem environments used in this work. See (Brockman et al., 2016) for a detailed description of control tasks.

Table 2: Pendulum observation space.

Num	Observation	Min	Max
0	x = cos(θ)	-1.0	1.0
1	y = sin(θ)	-1.0	1.0
2	$\dot{\theta}$ = Angular Velocity	-0.8	0.8

In this reward function, $\phi(\theta)$ is the difference between the current angle θ and the upright position angle, and torque is the control input applied to the pendulum. The term $\phi(\theta)^2$ penalizes deviation from the upright position, $0.1 \times \dot{\theta}^2$ penalizes high angular velocities to encourage smoother movements, and $0.001 \times \text{Torque}^2$ penalizes large control inputs to promote energy efficiency.

3.1.3 Cartpole Task

The Cartpole task involves balancing a pole on a cart by applying force to the cart to keep the pole upright. This task has 4 observation variables given by cart position (x), cart velocity ($\dot{x}$), pole angle (θ), and pole velocity at the tip ($\dot{\theta}$). As shown in Figure 1, the state of the Cartpole at every time step is given by the cart position and velocity, pole angle in radians (θ), and pole angular velocity. The action space is discrete and consists of two actions, which represent pushing the cart to the left or right. The observation space consists of four elements which are indicated in Table 3.

Table 3: Cartpole observation space.

Num	Observation	Min	Max
0	Cart Position	-4.8	4.8
1	Cart Velocity	-Inf	Inf
2	Pole Angle (θ)	-0.418 rad	0.418 rad
3	Pole Angular Velocity	-Inf	Inf

The reward function is t_{end}, with +1 awarded for each time step the pole remains upright. t_{end} is reached when the pole falls, the cart moves out of bounds, or the max number of steps is reached. The goal is to maximize the number of time steps the pole stays upright.

In all tasks, agent training fitness is its mean reward over 20 episodes, where each episode begins with random initial conditions and ends with success, failure, or reaching a time constraint. Post-evolution, the single training champion is reloaded and evaluated in 100 test episodes with initial conditions not seen during training.

Velocity state variables describe how the system is changing over time. To make these environments partially observable, we remove velocity state variables from the observation space. In order to control the systems without this information, agents **must** use temporal memory to store sequential observations over time and integrate this data to predict the velocity of the system. Note that predicting system velocities only requires short-term memory.

3.2 Tangled Program Graphs

Tangled Program Graphs (TPG) is a hierarchical algorithm for evolving teams of programs. The basic building block in TPG is a team of programs (see Figure 2). Each team represents a stand-alone decision-making entity (agent) in this framework. Each program is a linear structure consisting of registers and instructions that operate on observation inputs and internal memory registers. Programs return two values: a bid value and an action value. Teams follow a first-placed sealed bid auction method where the highest bidding program at each timestep wins the right to decide the action. This action could be a discrete value (directional forces in Figure 2), continuous value (contents of scalar register s[1] in Figure 2), or a pointer to another team. If the action is atomic (i.e. discrete or continuous) it is returned to the task environment as the control output for the current timestep. If the action is a team pointer, then decision-making is delegated and the bidding process repeats at this team for the same timestep and observation. The process repeats recursively until an atomic action is reached.

3.3 Memory

The TPG model introduced in (Smith and Heywood, 2019) features an external shared memory accessible to all agents. Each agent consists of several teams and programs, and each program has its own private reg-

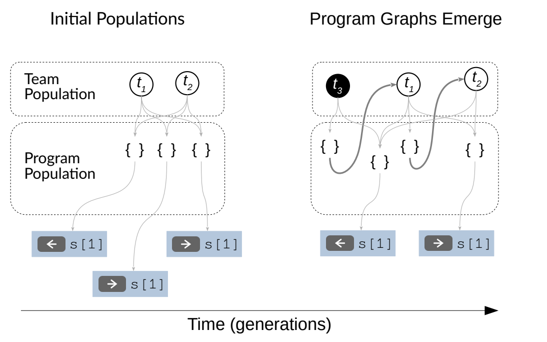


Figure 2: Tangled Program Graphs' hierarchical decision-making structure in which teams of programs predict discrete and continuous actions.

isters, which are inaccessible to other programs. Program registers are stateful, and thus provide a simple form of recurrent temporal memory. Furthermore, all programs have access to the shared external memory for reading and writing operations. This memory is not reset between training episodes or the evaluation of different agents, ensuring continuity and allowing for cumulative knowledge building.

Indexed memory operations are handled probabilistically to manage both short-term and long-term retention. The write operations distribute the content of a program's registers across the external memory in a probabilistic manner, with locations in the middle of the memory being updated more frequently (short-term memory) and those towards the ends being updated less frequently (long-term memory). This study uses the following probability definition, which is shown in Figure 3, and where i corresponds to the index:

$$P_{\text{write}}(i) = \frac{0.25}{0.5\pi(i^2+0.25)} \tag{2}$$

This function provides a heavy-tailed distribution, allowing writing across a wide range of memory locations, the probability is sharply peaked at the center and rapidly decreases as the offset increases.

Read operations use indexing, allowing programs to locate regions of external memory characterized by specific temporal properties. This approach allows programs to interact during each generation or across different generations, facilitating more sophisticated decision-making strategies.

4 EXPERIMENTS

The experiments detailed in this section are designed to evaluate our TPG shared temporal memory implementations in mitigating the negative impact of destructive agents while maintaining system performance and efficiency. We used TPG as implemented

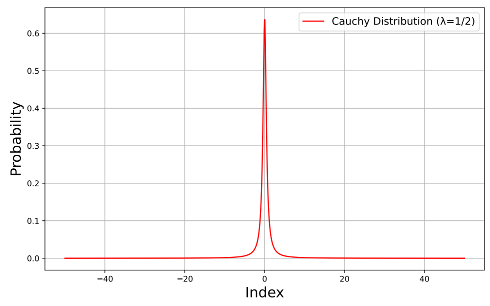


Figure 3: Probability function for memory write operations.

in (Amaral, 2019). The culture method discussed in (Spector and Luke, 1996a) highlights the negative impact of destructive agents, noting that while positive ideas from individuals can be preserved for collective benefit, negative actions by a single agent can destroy valuable information. To reduce this negative impact, we study the effect of clearing memory at different stages and compare the results with the original version of shared memory in TPG.

We assess three strategies: *resetting memory for each agent* (Section 4.1), *resetting memory for each episode* (Section 4.2), and a *no-memory* condition (Section 4.3). Algorithm 1 details the implementation of these strategies. The following terms are used in the pseudocode: `execute_frames()` executes a set of frames where the agent takes an action based on observations and receives feedback from the environment for each frame. **Lock pooling** and **release pooling** manage parallelism, with **lock pooling** preventing other agents from interacting with memory and **release pooling** restoring parallelism after the agent completes its interactions. `execute_episodes_with_frames()` runs multiple episodes.

4.1 Reset Memory for Each Agent

In this case, the external memory and registers are cleared and set to zero at the beginning of evaluating each agent in each generation. This method ensures that each agent can independently build its own memory model at run time and removes the possibility of negative impact from other agents. Each agent essentially has its own indexed memory which is shared among its programs, resembling a smaller society. In this case, the agent's memory maintains state over all training episodes, during which time the agent is free to gradually develop its mental model of the environment. While each agent interacts with memory, it is essential to restrict others' access to it. In our current implementation, this requires blocking the parallelizing system, which increases experiment run time.

Algorithm 1: Agent execution with memory resetting conditions.

```
for generation in generations do
    run agent with pooling
    if original_version then
        execute_episodes_with_frames()
    else
        if reset_for_each_agent then
            lock pooling
            reset external memory
            reset agent's registers
            execute_episodes_with_frames()
            release pooling
        else
            if reset_for_each_episode then
                for episode in episodes do
                    lock pooling
                    reset external memory
                    reset agent's registers
                    execute_frames()
                    release pooling
                end
            else
                for episode in episodes do
                    for frame in frames do
                        reset agent's registers
                        act and get feedback
                    end
                end
            end
        end
    end
end
Function execute_frames():
    for frame in frames do
        act and get feedback
    end
Function
 execute_episodes_with_frames():
    for episode in episodes do
        execute_frames();
    end
```

4.2 Reset Memory for Each Episode

This approach also removes potential negative impact of other agents. In this version, we reset the external memory and all the agent's registers at the beginning of each episode. This tests the agents' ability to build their memory quickly during a single episode. Again, when one agent interacts with memory, it is essential to restrict others' access to it.

4.3 No Memory

In this version, we do not use any external indexed memory and we clear all the agent's registers to zero at the beginning of each time step, implying the agent's behaviour is entirely stateless. This is a control experiment to confirm that all partially observable task configurations absolutely require stateful agents with temporal memory capabilities.

4.4 Experimental Parameters

Evolutionary hyper-parameters follow previous TPG work in RL tasks (Smith and Heywood, 2019). The initial root team population is set at 360 and remains static throughout evolution. We utilize "Cauchy Half" (Equation 2) for memory distribution in scenarios involving memory. The operation set includes: "ADD", "SUB", "MULT", "DIV", "NEG", "COS", "LOG", "EXP", "MEM_READ", and "MEM_WRITE" allowing complex interactions without any task-specific functions. To constrain model complexity and computational cost of decision-making, we set the probability of acting atomic to be 1.0, meaning no programs point to another team.

4.5 Results

Experiments reveal that the *reset memory for each episode* strategy (Section 4.2) improves the score and performance of TPG agents across all the control problems mentioned in Section 3.1, as shown in Figure 5. This memory configuration also results in the lowest solution complexity, as indicated in Figure 6.

We conduct experiments for all the cases detailed in Section 4 as well as the original version of PyTPG (Amaral, 2019), using the Cauchy Half distribution for memory writing probability. We ran 10 repeats with unique random seeds for Pendulum task and CartPole task, and 8 repeats for Acobot task. Each experiment was run using multiple cores to manage the computational load efficiently: 30 hours with 30 cores for Acrobot, 48 hours with 10 cores for Pendulum, and 72 hours with 20 cores for CartPole. The results were compared based on the achieved score during the same running period (Figure 4), reached score based on the number of generations (Figure 5), and their complexity (Figure 6). The complexity is characterized by average number of instructions executed per action decision.

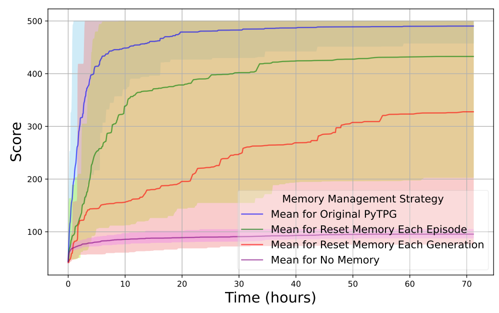
To plot Figures 5 and 4, we determined the minimum number of generations across all experiments. According to Figure 5, for all three environments, the approach of *resetting memory for each episode* has the best average score after the 5^{th} generation.

In Figure 6, the complexity over the minimum number of generations across all experiments is reported. This figure demonstrates that resetting memory and registers for each episode reduces complexity. Interestingly, in all three environments, although the *no memory* version has the worst score over generations, it exhibits the highest complexity. This indicates that agents are struggling to improve by making more complex decisions. On the other hand, the version with *resetting memory for each episode*, which has the highest score, also exhibits less computational complexity than the original PyTPG.

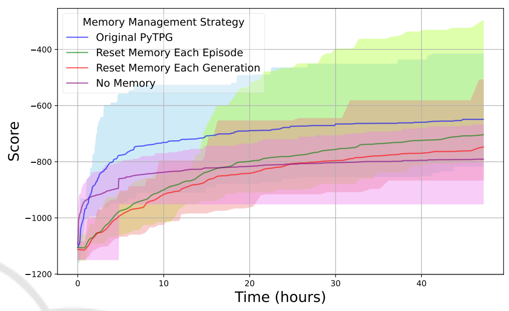
Execution speed varied across tasks: the *no memory* version consistently ran the most generations, indicating the fastest execution speed. The original version performed at an intermediate speed, while both the *reset memory for each agent* and *reset memory for each episode* versions were the slowest, running significantly fewer generations across all tasks due to the blocking of parallelism as discussed in Section 4. The blocking mechanism is further illustrated in Algorithm 1. The running time explains the original version's superior results over the same amount of time as indicated in Figure 4. However, since this version runs more generations in the same amount of time as *reset for each episode*, it achieves a better score. Still, based on Figure 5, it would perform worse if it operated at the same speed as the *reset memory for each episode* case.

These results support our hypothesis that, for tasks without long term state dependencies, resetting memory before each episode can reduce the effect of negative agents and improve results over the same number of generations. As expected, the *no memory* version cannot solve these partially observable tasks.

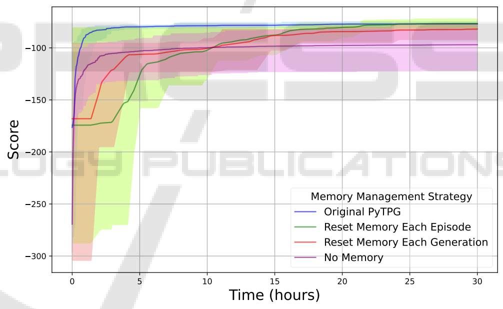
After training, we reloaded and tested the champion of the last common generations for each case across all seeds. We applied the Mann-Whitney U test to compare each case with the *reset memory for each episode* case, confirming the results in Figure 5 with p-values less than 0.05. In Acrobot, the *reset memory for each agent* and *reset memory for each episode* versions showed no significant differences due to similar scores. However, both versions showed significant differences (p-value$<$0.05) compared to the original and no-memory versions. Readers interested in further details about TPG and visualizations of evolved graphs of teams are referred to (Djavaherpour et al., 2024), (Smith and Heywood, 2024), (Kelly et al., 2021).



a Cartpole environment.



b Pendulum environment.



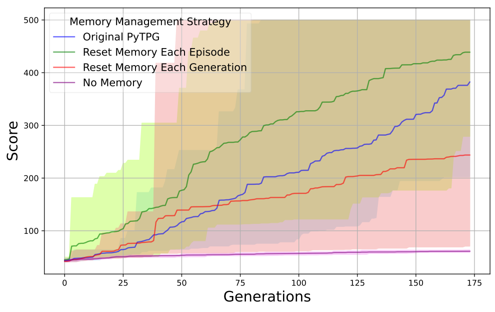
c Acrobot environment.

Figure 4: Scores achieved in different memory strategy experiments over 48 hours in various environments.

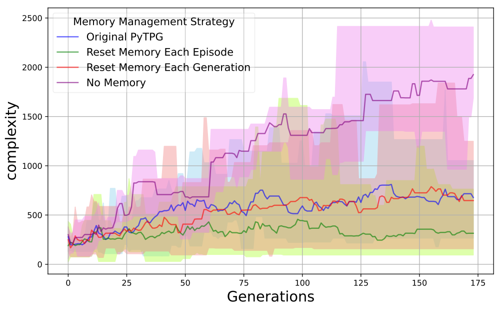
5 CONCLUSION

This study explored the effectiveness of different memory management strategies in enhancing the performance of Tangled Program Graphs in partially observable Reinforcement Learning environments. We experimented with TPG's original shared indexed memory formulation, resetting memory for each agent, resetting memory for each episode, and a no-memory condition across three benchmark tasks: Acrobot, Pendulum, and CartPole.

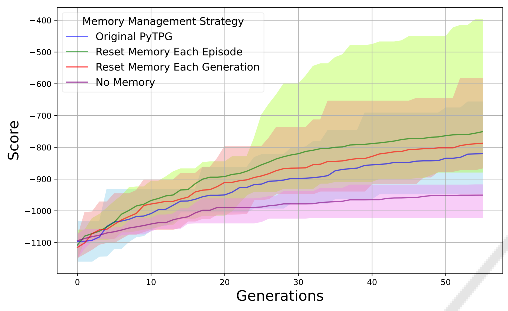
The results show that resetting memory for each episode improves the performance of TPG agents across all tasks. This strategy led to the highest av-



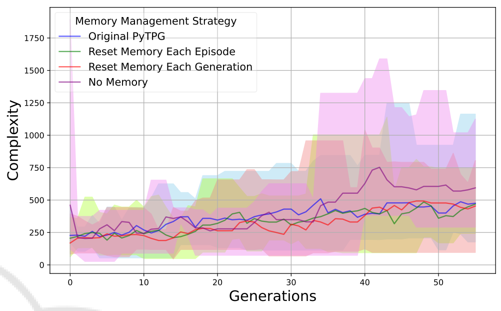
a Cartpole environment.



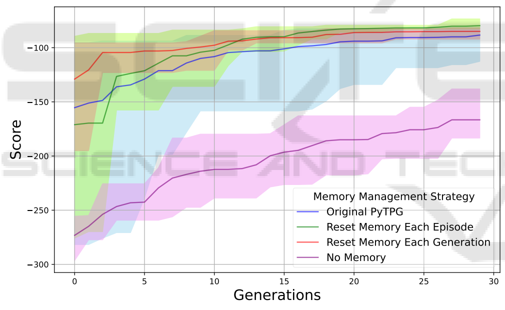
a Cartpole environment.



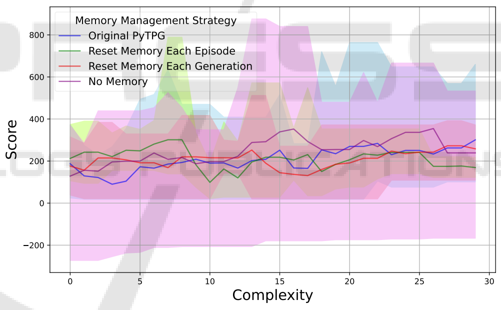
b Pendulum environment.



b Pendulum environment.



c Acrobot environment.



c Acrobot environment.

Figure 5: Scores achieved in different memory strategy experiments over 48 hours, based on the minimum number of generations run in various environments.

Figure 6: Complexity in different memory strategy experiments over 48 hours, based on the minimum number of generations run in the different environment.

erage scores after the initial few generations and reduced the complexity of decision-making processes. In contrast, the no-memory version, although capable of running more generations, struggled to solve the partially observable tasks effectively, exhibiting the highest complexity and lowest performance.

Interestingly, while the *reset memory for each agent* and *reset memory for each episode* strategies showed similar performance, both were significantly better than the original and no-memory versions in terms of robustness and reliability, demonstrating consistency of the agents' performance across different runs with a tighter distribution of scores over the repeats. In contrast, the *reset memory for each generation* case failed to perform better than the original version in CartPole only. The Mann-Whitney U test confirmed these findings, with p-values less than 0.05, indicating significant differences.

These findings suggest that shared memory and "culture" can have a negative impact on the performance of TPG agents in partially observable tasks with no long term temporal dependencies. Resetting memory before each episode can mitigate these negative effects, improving agent performance and reducing decision-making complexity. However, the primary drawback of the memory reset strategies is the increased runtime due to the blocking of parallelism. Implementing a dedicated memory for each agent could potentially mitigate this issue, allowing parallel execution without interference and maintaining computational efficiency.

Overall, effective memory management strategies are crucial in reinforcement learning tasks. By carefully selecting and optimizing memory resetting strategies, significant improvements can be achieved in the efficiency and effectiveness of TPG in challenging control environments.

6 FUTURE WORK

Future work will scale these experiments to more complex environments, such as Memory Gym (Pleines et al., 2023), in order to validate the methods' robustness and explore their adaptability to tasks with long and short time dependencies. The current memory strategies help agents quickly build mental models without directly sharing information. However, this may not be suitable in complex tasks where global memory is beneficial (e.g. (Smith and Heywood, 2019)). For such cases, we envision a dynamic method, such as resetting memory based on real-time performance metrics (e.g., wiping memory if median score drops below that of the previous generation), could provide a more adaptive approach. Additionally, investigating other probabilistic memory functions and their combinations could provide further insights into optimizing agent's memory use. For example, rather than manually resetting memory, it might be possible to *evolve* customized memory management rules for each agent which automatically minimize negative effects on shared memory. Finally, integrating advanced parallelization techniques could mitigate the runtime overhead caused by memory resets, improving their practicality in real-world applications. Since this paper incurred significant wall clock run time, faster TPG frameworks, such as those from (Djavaherpour et al., 2024), will be considered for use in future work.

Overall, studying the long-term evolutionary impacts of different memory strategies could provide deeper insights into the development of more sophisticated and adaptive agents in partially observable environments.

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