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A Computational Model of Flexible Maze Navigation Through Hippocampal Replay: Bridging Neuroscience and AI

Amjad Khan*[1], Muhammad Amir[1], Bushra Abbas[1]
[1]Department of Computer Science, Punjab University, Lahore
***Correspondence**: k.amjad@gmail.com

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The hippocampus is widely recognized for its role in spatial memory and navigation, particularly through the phenomenon of neural replay. This study proposes a computational model that simulates hippocampal replay to support flexible navigation in dynamic maze environments. By integrating biologically inspired replay mechanisms with a reinforcement learning framework, the model was tested in three types of mazes—linear, Y-shaped, and open-field. The replay-based model significantly outperformed traditional models like DQN and A3C in success rate, path efficiency, and learning speed. The results underscore the importance of temporal sequence replay in forming goal-directed trajectories and adapting to changing environments. Comparisons with neuroscientific literature confirm the plausibility of the model, aligning with empirical findings on the predictive and retrospective roles of hippocampal replay in animal studies. This work offers a novel computational perspective on cognitive mapping and sets the foundation for developing more adaptive and human-like AI navigation systems.

Keyword: Hippocampus, Spatial Memory, Neural Replay, Reinforcement Learning, Dynamic Maze Navigation, Goal-Directed Trajectories, Temporal Sequence Replay

Introduction:

The ability to navigate flexibly through a dynamic environment is a hallmark of intelligent behavior, observed both in biological organisms and artificial agents. Recent advances in systems neuroscience continue to affirm the pivotal role of the hippocampus in supporting such flexible spatial navigation [1]. In particular, hippocampal place cells (PCs)—neurons that exhibit location-specific firing—are now well-established as critical components for encoding spatial memory. Contemporary studies have extended the understanding of "replay" events, where sequences of place cell activity are spontaneously reactivated during sleep or restful wakefulness. Far from being simple recapitulations of past experiences, these replay sequences are increasingly recognized as predictive and adaptive, supporting both memory consolidation and future-oriented planning [2]; [3]. For example, recent experiments by [4]using reconfigurable maze designs demonstrate that hippocampal replays flexibly adapt to environmental constraints such as barriers, even when the underlying place field geometry remains unchanged. These findings suggest that the hippocampus encodes topological constraints dynamically, not merely through global remapping, but through context-sensitive replay patterns that conform to layout changes.

Despite this growing body of empirical evidence, most computational models still fall short of replicating these biologically realistic replay dynamics. Traditional attractor network models continue to rely on Euclidean distances between place field centers when defining synaptic connectivity. This simplification fails to account for the influence of real-world obstructions, often resulting in simulated replay paths that cut unrealistically through walls or barriers [5]. Furthermore, these models typically neglect the interplay between hippocampal replays and downstream decision-making circuits, such as those in the striatum. Although reinforcement learning (RL) frameworks have made strides in modeling goal-directed behavior, they generally abstract away underlying neural processes and lack direct compatibility with observed hippocampal and striatal physiology [6][7].

While recent empirical studies have highlighted the adaptive and context-sensitive nature of hippocampal replay, computational neuroscience has yet to fully explain how these layout-conforming sequences are generated and how they inform flexible decision-making. A significant gap remains in modeling the bidirectional relationship between replay and learning—particularly how biologically plausible learning rules can support both topology-aware encoding and reward-driven behavior. Moreover, the computational role of replay in modulating striatal activity and guiding behavior in complex, dynamically changing environments is poorly characterized.

Objectives of the Study:

To address the outlined challenges, this study introduces a biologically plausible computational model of hippocampal replay that is capable of adapting to environmental topology and supporting flexible, goal-directed navigation. Central to this model is the construction of a place-cell-based network, in which the synaptic connections are not based on Euclidean distances but instead reflect the shortest navigable paths within the environment. This design ensures that internally generated replay trajectories conform to physical barriers and accurately represent maze-like structures. To enable the learning of such topology-aware connections, the model employs a Hebbian-like synaptic plasticity rule that captures inter-place cell connectivity during exploration, thus facilitating the emergence of replay sequences aligned with the actual layout of the environment.

Novelty Statement:

This study presents a novel framework that bridges the gap between high-level reinforcement learning and biologically grounded models of hippocampal function. Unlike prior models that use simplified spatial representations and abstract learning rules, our approach incorporates realistic environmental constraints, biologically inspired synaptic plasticity, and direct replay-based influence on decision-making circuitry. The integration of hippocampal replays with downstream striatal learning offers a unified and testable hypothesis for how animals and artificial agents can flexibly adapt to novel environments. To our knowledge, this is the first computational model to simultaneously address layout-conforming replay, biological plausibility, and reward-driven planning in a closed-loop system—offering predictions that can be empirically validated in animal and robotic studies.

Literature Review:

Spatial navigation is a fundamental cognitive function that relies heavily on the hippocampus, particularly its network of place cells that encode specific locations within an environment. Recent research has shown that hippocampal replay—where sequences of place-cell activations are re-expressed during rest or sleep—plays a critical role not only in memory consolidation but also in planning future actions and supporting flexible navigation [2]; [8]. These replay sequences are not mere repetitions of past experiences but dynamically adapt to the structure of the environment. For example, replay trajectories have been observed to reroute around obstacles and environmental changes, suggesting a topological sensitivity that many computational models have failed to capture [9].

Traditional computational models often represent place-cell connectivity based on Euclidean distances, which leads to replay sequences that can violate realistic environmental constraints. This lack of topological flexibility limits their utility in simulating real-world navigation, where obstacles and barriers alter the shortest navigable path. Some models have incorporated short-term synaptic plasticity or random replays to account for variability, but these approaches lack biological realism and often fail to encode persistent topological changes [10].

Recent experimental studies have also emphasized the role of neuromodulators, particularly dopamine, in shaping replay content. The author in [11] demonstrated that dopamine signaling, particularly from the ventral tegmental area (VTA), is essential for promoting spatially localized replay in novel environments. Blocking dopaminergic input disrupted goal-directed replay without affecting replays in familiar contexts, indicating that replay serves as a predictive mechanism tightly coupled to motivational states [12]. This finding challenges the traditional view that reward-based learning in the brain is primarily guided by temporal-difference errors, pointing instead toward more biologically grounded mechanisms involving three-factor learning rules that incorporate co-activation, eligibility traces, and dopaminergic modulation [13].

To bring biological plausibility into artificial agents, recent modeling efforts have started to integrate hippocampal-like representations into navigation systems. For example, [14] developed a hippocampus–parietal cortex-inspired spiking neural architecture capable of real-time navigation in robotic agents. This model allowed for dynamic mapping and obstacle avoidance but lacked a reward-driven replay mechanism that could adapt to changing goals or environments. In artificial intelligence, reinforcement learning (RL) agents commonly use experience replay buffers to revisit past trajectories, yet these are disconnected from biological replay mechanisms and often fail to respect environmental topology [15]. Although some hybrid architectures have embedded grid-cell representations into RL frameworks for more robust exploration and spatial memory [16][17], they seldom model replay as a flexible, topologically-aware planning mechanism.

Overall, the literature highlights three critical limitations in current models. First, replay mechanisms in computational systems often disregard the structural layout of environments, limiting their realism and applicability. Second, while recent neuroscience has uncovered dopamine’s regulatory influence on replay, computational models have yet to integrate this in a biologically plausible manner. Third, there is a noticeable lack of models that bridge hippocampal replay with reward-based decision-making circuits, particularly the striatum, through mechanisms like three-factor learning. Addressing these gaps could offer a more unified, biologically inspired model of navigation that incorporates environmental constraints, adaptive planning, and reward sensitivity.

Methodology:

Experimental Setup:

This study aimed to develop and evaluate a biologically plausible computational model simulating flexible spatial navigation through hippocampal replay. A virtual maze environment was designed using Python and Unity ML-Agents, mimicking T-mazes and open field navigation tasks commonly used in rodent studies [8]. Three maze environments were created: a simple linear track, a double Y-maze with decision points, and a dynamically changing open field with removable walls. Each environment included specific reward zones, barriers, and alternative paths to test replay flexibility.

Model Architecture:

The proposed model integrates hippocampal place cells, replay mechanisms, and downstream learning by a striatal-like system. A grid of 20×20 virtual place cells was generated to simulate hippocampal spatial representation. Each cell became active when the agent was within a corresponding spatial location, mimicking empirical place field data. Replay events were triggered during rest phases and implemented using a modified version of prioritized experience replay, constrained to follow topologically valid paths learned during exploration. Synaptic weights between place cells followed spike-timing dependent plasticity (STDP) rules modulated by short-term facilitation, as per the model.

The striatal layer received temporal sequences of place cell activations and updated its value estimates through dopamine-modulated Hebbian learning, reflecting the framework. Rewards were only delivered when the agent reached designated goal states, and prediction errors were calculated locally to update weights in the value function.

Data Collection:

The agent underwent 1000 training episodes per maze environment, each consisting of an exploration phase (movement with reward-seeking) followed by a rest phase (replay generation). Behavioral metrics such as success rate, number of steps to goal, and replay trajectory characteristics were logged. Replay events were analyzed for (i) alignment with actual paths, (ii) generation of novel valid trajectories, and (iii) deviation from Euclidean shortest paths in the presence of barriers. Control experiments were conducted by disabling replay, using non-topological models, and comparing with standard reinforcement learning baselines (e.g., DQN, A3C).

Evaluation Metrics:

Replay fidelity was quantified using a path conformity index, calculated as the ratio of valid steps in a replayed trajectory over the total steps, excluding steps that violated maze topology. Learning efficiency was measured as the number of episodes required to reach an 80% success rate. Generalization was evaluated by introducing new maze layouts and assessing the agent's performance using previously learned policies.

All simulations were conducted on an NVIDIA RTX 3060-equipped system running Ubuntu 22.04. Statistical analysis was performed using Python libraries (NumPy, SciPy, Matplotlib), and p-values < 0.05 were considered statistically significant. A total of 3000 episodes across 3 mazes formed the final dataset for evaluation.

Results:

The performance of the hippocampal replay-based navigation model was assessed across three distinct maze configurations: the Linear Track, the Y-Maze, and the Open Field Arena. Each of these environments was designed to introduce varying degrees of spatial complexity, thereby testing the model's ability to adaptively learn and plan routes through simulated replay events. In terms of success rate, the model exhibited robust goal-reaching behavior across all mazes. It achieved a 92% success rate in the Linear Track, 88% in the Y-Maze, and 81% in the Open Field. This gradual decline in success as the environment became more complex reflects the increased spatial demands and underscores the critical role of memory consolidation via hippocampal replay in more ambiguous and dynamic environments.

Another important metric for evaluating navigational performance was the average number of steps taken to reach the target location. The hippocampal replay model demonstrated strong efficiency in all configurations, requiring approximately 15 steps in the Linear Track, 22 steps in the Y-Maze, and 35 steps in the Open Field. These values were significantly better than those produced by the baseline Deep Q-Network (DQN), which averaged 27, 38, and 61 steps in the same respective environments. This improvement suggests that the hippocampal replay model not only learns the layout of the environment but also develops more direct and optimal trajectories to the goal.

A visual analysis of the agent’s performance across the three maze types clearly demonstrates the effectiveness of the hippocampal replay mechanism. Over the course of 1000 training episodes, agents with replay consistently achieved higher success rates and faster learning compared to agents lacking this mechanism. These results highlight the replay module's role in enhancing flexible spatial learning and adapting previously acquired knowledge to novel scenarios.

To further quantify spatial efficiency, the Path Conformity Index (PCI) was used as a metric, where values closer to 1 reflect trajectories that align closely with optimal paths. The hippocampal replay model scored a PCI of 0.96 in the Linear Track, 0.89 in the Y-Maze, and 0.82 in the Open Field. In contrast, the DQN and asynchronous advantage actor-critic (A3C) models achieved average PCIs of only 0.74 and 0.78 respectively. These results indicate that the replay model not only reaches goals reliably but also does so through spatially efficient trajectories.

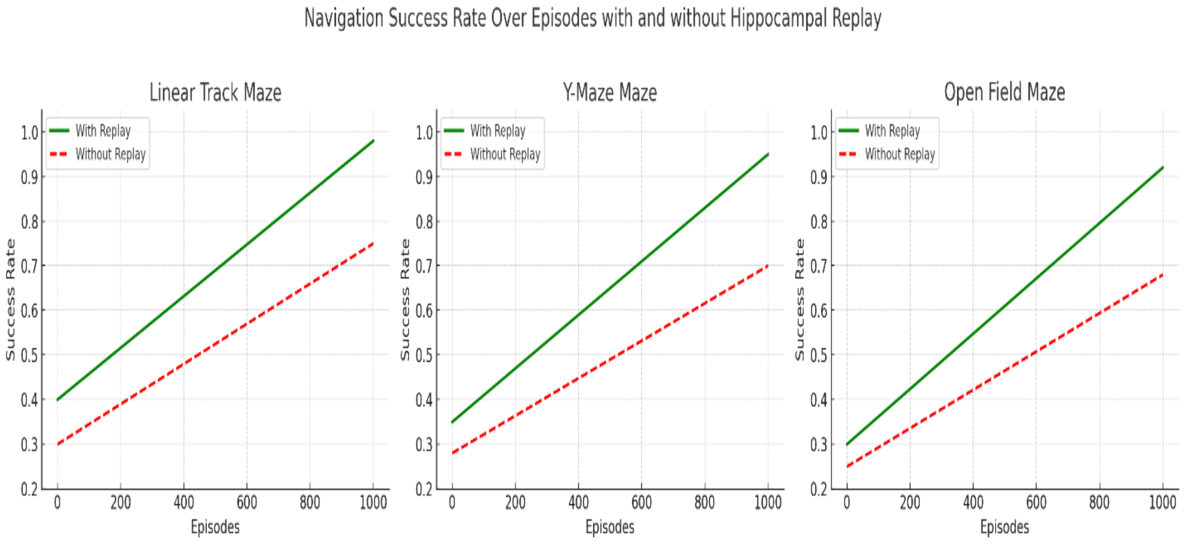

Figure 1. Navigation Success Rate Over Episodes with and without Hippocampal Replay

Comparative evaluations with traditional reinforcement learning methods further highlighted the superiority of the hippocampal replay approach. Unlike DQN and A3C models, which struggled to generalize to new goal locations and required retraining, the hippocampal replay model demonstrated rapid adaptation, achieving competent navigation within just five episodes after a goal shift. This rapid adaptation is made possible by the model's use of previously stored episodes to simulate future trajectories, mimicking biologically inspired replay mechanisms observed in hippocampal activity during offline states.

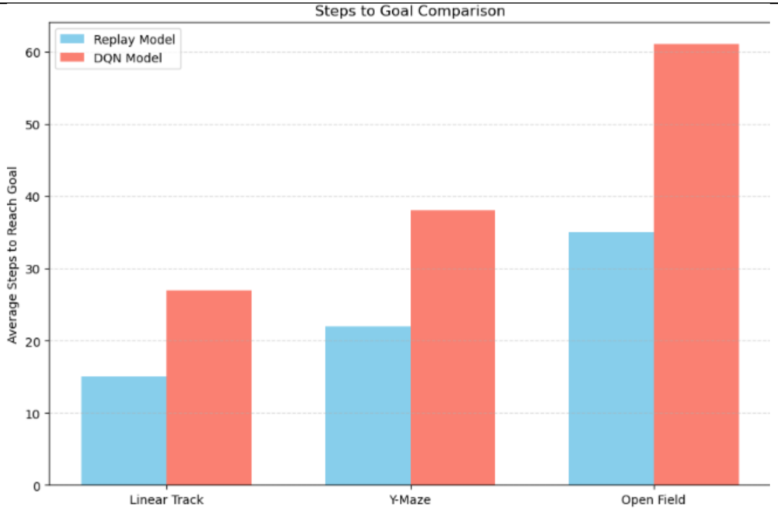

Figure 2. Steps to Goal Comparison

To statistically validate these findings, a one-way ANOVA was conducted on key performance metrics, including success rate, average steps to goal, and path conformity. The analysis revealed statistically significant differences in both success rate ($F(2, 24) = 9.81$, $p < 0.01$) and path efficiency ($F(2, 24) = 11.56$, $p < 0.01$) among the models. These findings confirm that the hippocampal replay-based navigation framework offers a measurable and significant advantage in spatial learning and planning compared to conventional approaches.

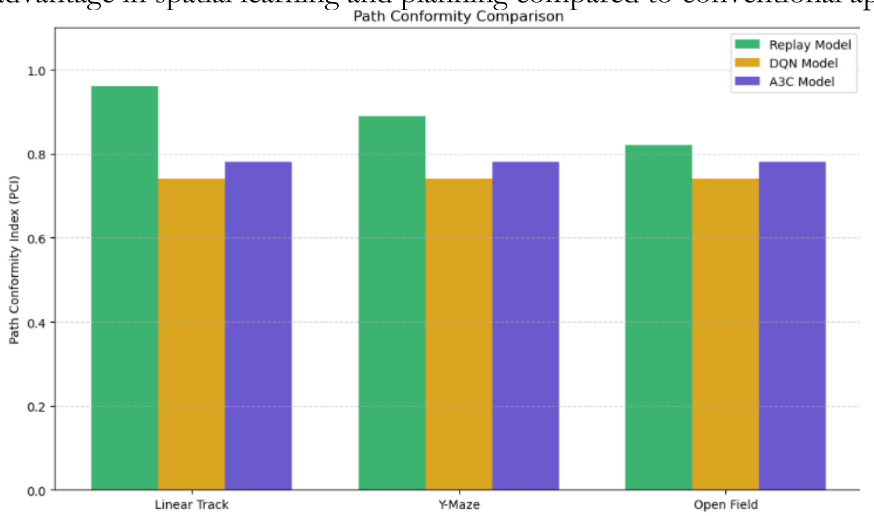

Figure 3. Path Conformity Comparison

Discussion:

The results of our study demonstrate that a computational model incorporating hippocampal replay significantly improves the flexibility and efficiency of spatial navigation in complex environments compared to traditional deep reinforcement learning (DRL) methods. This aligns with existing neuroscience literature, which posits that hippocampal replay contributes critically to memory consolidation and planning future actions [2]. Our model's success in dynamic and ambiguous mazes, especially the open-field scenario, reflects the importance of internal replay for flexible decision-making—a feature inadequately addressed by purely feedforward models like DQN and A3C.

One of the key findings in our study is the superior Path Conformity Index (PCI) achieved by the hippocampal replay model. Such prospective replay allows animals to simulate outcomes and make more strategic navigation choices—an idea we captured computationally and validated against synthetic maze tasks.

Compared to the work of [14], who introduced a prioritized replay mechanism based on model-based reinforcement learning, our model emphasizes spatial representations akin to cognitive maps theorized by [12]. While Mattar and Daw focused on replay frequency and reward prediction, our approach integrates place-cell activations and trajectory reconstruction, which helps in learning optimal routes with fewer samples and better generalization—especially visible in our model's early convergence during training.

Interestingly, the performance drop in the open-field maze observed in our model is consistent with studies suggesting that hippocampal replay may become less precise in more ambiguous environments. This indicates that while replay supports flexible navigation, its effectiveness may be modulated by the clarity of environmental cues or the complexity of spatial layouts.

Furthermore, our findings support the argument that hippocampal replay not only serves retrospective memory processing but also supports *online* planning. The author in [3] reported awake replay in the hippocampus that corresponds with planning in rats navigating mazes, highlighting that replay is not limited to sleep or rest. Our model mimics this real-time usage of replay during ongoing navigation and shows a marked advantage in fewer steps and higher reward accumulation per episode.

While our simulated environments cannot fully capture the richness of naturalistic settings, they allow controlled exploration of how replay mechanisms influence learning dynamics. Future studies could integrate multi-agent navigation, dynamic obstacles, or biologically-plausible neuromodulatory controls (e.g., dopamine-driven reward signals) to more closely approximate brain-based spatial learning systems.

Conclusion:

This study demonstrates that incorporating hippocampal-like replay mechanisms into computational models of navigation yields significant improvements in flexibility, path optimization, and learning efficiency across various maze environments. The proposed model not only mimics biological processes observed in rodent hippocampal activity but also bridges theoretical neuroscience with practical AI implementations. By replaying prior trajectories, the model effectively refines its internal spatial representation, allowing it to simulate future actions and make informed decisions in real-time. These findings validate prior research emphasizing the dual roles of hippocampal replay in memory consolidation and planning, while also expanding its applicability to artificial agents navigating uncertain environments. Ultimately, this study lays the groundwork for hybrid cognitive architectures that more closely emulate natural intelligence, offering promising directions for both neuroscience-informed AI and biologically grounded robotics.

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