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Bridging Classical Conditioning and Deep Reinforcement Learning: Advancements, Challenges, and Strategies for Autonomous Systems

Abstract: - Many systems rely on Artificial Intelligence (AI), especially Deep Learning (DL), even though it is rarely used on its own to complete tasks. DL makes use of the Markov decision process as a framework for efficiently learning tasks. Theoretically, this procedure is similar to classical conditioning, which is how animals learn to connect actions and stimuli to goals. Deep Reinforcement Learning (DeepRL) was used in several studies to test DL skills in a variety of video games, showing that this technique can adapt to different tasks with little modification. However, those studies encountered major obstacles because of its large data requirements and expensive computational expenses, even if it was successful. Building on this, we examine the relationships between classical conditioning and DeepRL. Through careful manipulation of variables such as hyperparameters and maze designs, a robot was trained to navigate mazes as part of the experiment. DeepRL is not autonomous in this paradigm because the results showed that the Markov decision process and classical conditioning experience comparable challenges in tasks involving advanced planning and goal identification. The study also identifies the key areas that require improvement, highlighting the shortcomings of existing AI systems and offering strategies for boosting their autonomy.

Keywords: Artificial Intelligence, Deep Learning, Deep Reinforcement Learning, Robot

1. Introduction

Artificial Intelligence (AI) has been progressively incorporated into systems that were previously run entirely by humans as a result of major cost and computational power reductions brought about by technical developments [1]–[3]. But, in the majority of these uses, AI enhances existing system components rather than taking over total control of activities. Robots, for example, often make use of AI-driven image recognition as just one input among many in a system with controls that were created by humans. This point up a significant drawback—not many AI techniques can supervise and manage projects from beginning to end. Prominent corporations and research institutes are pushing hard to improve the efficiency of AI systems. These organizations usually rely on large-scale datasets and high-performance computing to push the limits of AI, which makes their research difficult to replicate. While these methods have shown some amazing new capabilities, they also highlight the need for simplified experimental designs that can show AI techniques' effectiveness more clearly. AI has a wide range of possible uses in industries like—healthcare, and agriculture [4]–[16]. Exploring AI's potential is extremely important since advancements in AI technology could have a big impact on all of these industries. In addition to finding solutions to current issues, the main objective of AI research is to get technology closer to autonomous problem-solving. Considering Deep Reinforcement Learning (DeepRL) to be the state-of-the-art in robotics, this study attempts to explore the current status of AI technology. An extensive grasp of the main categories of Deep Learning (DL), an evaluation of their benefits and drawbacks, and an exploration of their real-world uses are all provided by this experiment. This study has the following particular goals in mind:

- To precisely characterize autonomous AI.
- Reviewing the DeepRL and neural network frameworks, outlining their features, functions, and uses.
- To look into the relation between classical conditioning and the Markov decision process, a mathematical framework for making decisions in the face of uncertainty.
- To present the latest achievements of cutting-edge AI systems, emphasizing important discoveries and their ramifications.

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- To create and carry out a reliable experiment that explore the concept—robot task performance, adaptability, and navigational abilities shared by both DeepRL and classical conditioning.

By achieving these goals, the study aims to offer insightful information that will aid in the creation of AI systems that are more independent and able to manage difficult jobs with less assistance from humans. The results are anticipated to contribute to the theoretical foundation of AI and offer useful recommendations for future applications of AI across a range of industries. To push the limits of what these technologies can accomplish, it is essential to comprehend the inherent strengths and weaknesses of AI. This effort tries to map out a future trajectory for AI breakthroughs that may eventually lead to completely autonomous systems through critical analysis and rigorous experimentation. This study aims to redefine the fundamental characteristics of problem-solving within the AI domain, rather than merely augmenting the capabilities of AI. The end objective is to move from AI systems that execute discrete—specialized tasks to ones that have the broad decision-making and learning capacities required for complete autonomy. Although there are many and compelling potential benefits for society, this change will require overcoming considerable theoretical and technological obstacles.

The study is as follows; similar papers are shown in the following section. The methods and materials are detailed in Section 3. The experimental analysis is carried out in Section 4. The findings are reported in Section 5, and the study is concluded with some conclusions and ideas for further research in Section 6.

2. Related Works

The field of developmental and cognitive robotics, which combines the fields of developmental psychology, neurology, and robotics, has advanced significantly in the last twenty years. This field has tackled complex AI challenges by using computational modelling extensively to comprehend and mimic the autonomous learning and development processes observed in human newborns such as [17], [18]. The key components of this advancement are the systems that encourage active exploration in large, unstructured spaces. The maturity of cognitive processes, goal-directed exploration, social learning, curiosity and intrinsically motivated Reinforcement Learning (RL), and the embodiment of sensory and motor systems are a few of these [19]. The development of incremental and online models that improve the robot's capacity for long-term learning and adaptation depends on these components such as [20], [21]. Self-directed free play and curiosity are two examples of intrinsically motivated behaviors that have had a significant impact. These actions provide robotic systems the ability to choose objectives and carry out tasks that optimise their learning capacity on their own such as [22], [23]. This strategy is based on the "child-as-scientist" idea, which suggests that a child—or, in this example, a robot—explores the world by taking small, methodical steps towards understanding it and trying to predict and manipulate its surroundings out of a natural curiosity.

Empirical studies such as [24], [25] demonstrated that this type of spontaneously driven inquiry contributes to the structuring of lifelong learning in a manner consistent with human developmental stages. Using the physical characteristics of the vocal apparatus in conjunction with intrinsic motivation, it is possible to model and comprehend, for example, the order in which infants acquire the ability to speak. Adopting these principles has prompted the creation of new experimental paradigms in neuroscience and psychology such as [26], [27], so providing evidence in favor of the theories on the ways in which intrinsic motivation influences learning and development. These intrinsic motivational concepts help robots accomplish complex tasks like omni-directional movement on slick surfaces and precise handling of soft things by enabling effective multitasking in high-dimensional areas. These tasks are controlled by parameterized tasks and stochastic selection of experiments, which aid in the incremental updating of skill models and the collection of valuable data. Through the efficient creation of an autonomous learning curriculum, [28] approach ensures ongoing learning and adaptability by controlling the increase in task complexity.

To further handle difficult situations with uncommon or deceptive rewards, new developments in DeepRL have started to incorporate processes of intrinsic motivation such as [29], [30]. Simpler RL situations have been achieved by adding auxiliary activities in addition to primary objectives. [31] shown how intrinsic motivation can be used to improve learning effectiveness and efficiency. Nevertheless, combining contemporary DeepRL systems with models of intrinsic motivation from developmental robotics offers plenty of untapped possibilities. Curiosity-driven issue selection and learning methodologies, as well as the fusion of intrinsic motivation and social learning, are prospective domains for further investigation. These are interesting directions to take the field in terms of advancement that have not yet been thoroughly investigated in the context of DL. The importance of embodiment in learning is a further important topic covered. The self-organization of learning behaviors is fundamentally influenced by the physical embodiment of learning agents, whether they are biological or artificial. [32] mimic human motions or baby hand-eye coordination demonstrate how organized learning can be induced without explicit computation through the interaction of a robot's physical shape with its surroundings. [33] demonstrate how physical limitations and features can greatly simplify learning processes, an idea that is still underutilized in most current AI research that focuses mostly on virtual environments. To sum up, cognitive and developmental robotics keeps improving robotic and AI systems by incorporating valuable knowledge from human developmental science. The secret to building more efficient, autonomous, and adaptable robots is to integrate self-organized learning, embodiment, and intrinsic drive. This integration not only increases the complexity of robotic systems' ability to do difficult tasks autonomously, but it also parallels the complexity of human learning.

3. Materials and Methods

This study uses Numpy, PyTorch 1.8.1, Python 3.9.9, and other complex programming frameworks to explore the connection between DeepRL and classical conditioning. However, to function on both CPUs and GPUs, the computational models are adaptable to a wide range of hardware configurations. Understanding hyperparameters—constants set by the designer to regulate the learning behaviour of AI methods—is a vital component of this study. In contrast to the internal network characteristics like weights and biases, we include eligibility trace constants, learning rates, and discount factors. Another important area to focus on in RL is the exploration vs. exploitation conundrum. In order to achieve this, one must strike a balance between taking known activities and exploring new ones to maximise rewards. To ensure that AI models do not settle too quickly on a presumptively optimal approach without enough examination, each method contains a stochastic element to maintain non-deterministic actions at any timestep. With the use of a network structure where inputs activate a Hebbian network[2] that chooses actions depending on the neuron with the highest value, the Reward Modulated Hebbian Learning (RMHL) method mimics classical conditioning. Using Gaussian noise to promote exploration, the system modifies its weights in response to reward input. To provide steady learning over time, a major adjustment that is motivated by Oja's rule[3] adds a normalization term to stop weights from rising exponentially. Within the actor-critic design is the adaptive critic element, which draws inspiration from biological incentive systems. In particular, in environments with sparse rewards, this model smooths the reward function by differentiating actions (Actor) and evaluating them (Critic) to improve the learning process based on internal reward estimations. Time-division equations improve the Critic's learning by offering an ongoing learning loop that adjusts according to expected state values. The epitome of modern AI research, DeepRL is demonstrated by a number of models, such as Q-Learning with experience replay, policy gradient, and advantage actor critic approaches. By using experience replay, which facilitates learning from a wide range of previous activities, Q-Learning is able to manage large state spaces. By estimating values using two networks, the double deep Q-Learning model reduces volatility in the learning process and stabilises learning. Using episodic memory to modify behaviors based on cumulative rewards, the policy gradient approach directly learns policies through gradient descent. To provide a probability distribution of actions, it uses a softmax function. This ensures that no action has a 0% probability of being selected, which makes exploration and exploitation easier. Last but not least, the advantage actor critic technique integrates value and policy approaches, changing policies and computing losses simultaneously. This approach uses temporal differences to inform real-time strategy modifications, optimizing both the evaluation (Critic) and decision-making (Actor) processes. The study seeks to advance our understanding of autonomous AI in complex circumstances by examining these advanced AI models and shedding light on the similarities and differences between artificial and biological learning systems. By incorporating the concepts of classical conditioning into AI frameworks, learning algorithms become more resilient and artificial learning processes become more in line with natural intelligence systems.

4. Experimental Analysis

This study assesses the performance of DL techniques on the OpenAI Gym, a benchmarking platform created to evaluate algorithms for RL in diverse settings. Three distinct environments are explicitly tested in this study—pong, cart pole, and lunar lander. These environments were selected based on their varied state values, reward systems, and action ranges. These settings give researchers a thorough environment in which to evaluate and comprehend the strengths and weaknesses of various AI techniques in standardized circumstances. For the lunar

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[2] Hebbian networks are neural networks that represent the idea that "cells that fire together, wire together" by fortifying connections between neurons based on simultaneous activation.

3 According to Oja's rule, synaptic weights in neural networks fluctuate in response to eigenvector changes and neuron activity.

lander and cart pole games, there are ten trials each, and for pong, because it takes longer to process, there are three trials for each game in the experimental technique. Every environment follows a set of rules that determine whether it wins, loses, or times out, which ends the episode. The models are built to run on both CPUs and GPUs to maximize processing times, and the implementations make use of Python 3.9.9, PyTorch 1.8.1, and Numpy. Among the AI techniques examined are Advantage Actor Critic (A2C), Deep Policy Gradient (DPG), and Deep Q-Network (DQN). These techniques use ReLU activation functions and AdamW for optimization, which is a modified version of stochastic gradient descent that speeds up learning. The agent's mission is to maneuver a spaceship between two flags and land it safely in the lunar lander environment. Through the use of thrusters, the agent modifies the lander's position and speed. Overuse of the downward thruster results in a deduction of points; nevertheless, landings and touch-downs that are successful and leave the landing gear intact are awarded. The DPG approach modifies the reward scale from -1 to 1 in order to preserve consistency in the learning objectives. The position, velocity, angle, angular velocity, and state of contact between the landing gear and the ground are among the inputs that the agent gets. In the cart pole scenario, an agent has to maintain an upright pole balance on a rolling cart, posing a basic control problem. To keep the pole in its upright position, the agent adjusts the cart's left and right movements. As long as the pole stays straight, points are continuously awarded by the reward system. The DQN approach is given a modified reward function that equivalences all states' values unless the pole crashes, with the agent receiving a penalty of -1 for failing. The third environment, ping pong, presents a difficult task. In order to pass the ball past the opponent's paddle and into the goal, the agent must control a paddle while playing against them. Simplexes and scaled game pixel inputs are processed by the agent in order to expedite computation. Convolutional Neural Networks (CNNs) are used in the pong learning model, which collects information from the images in order to classify them effectively. This arrangement improves the agent's forecasting powers by utilizing previous frame sequences to forecast the ball's path. The objectives of these settings and the difficulties they present are to assess each algorithm's performance in reaching high scores as well as its capacity to adapt and learn from new experiences. In order to provide light on how AI models interpret data, make choices, and adjust course in response to feedback, the study attempts to identify the advantages and disadvantages of each learning strategy.

5. Result Analysis

With an emphasis on three distinct environments—lunar lander, cart pole, and pong—the study uses the OpenAI Gym [4]to examine how well DeepRL algorithms perform. AI learning capabilities are tested in each setting in a variety of ways, from adaptive incentive schemes to action execution. The purpose of the study is to examine the strengths and limitations of these algorithms and to comprehend how they manage challenging tasks. The DQN, which achieved 200 points in 500 episodes, demonstrated the highest peak results in the lunar lander experiment as shown in Fig. 1(a). Overfitting caused the network to memorize certain input-output combinations rather than learning to generalize from the data, which is why its performance decreased over time. The algorithm's poor performance was a result of its over-specialization, which prevented it from adapting to the task's wider requirements. The A2C showed slower learning and failed to converge within 5000 episodes due to a bottleneck caused by the critic's requirement to evaluate actions before the actor could learn efficiently, whereas the DPG algorithm learned at a steady rate and reached a stable performance level. DQN demonstrated a rapid reach and maintenance of a local minimum performance level in the cart pole control problem as shown in Fig. 1(b), indicating that further time or hyperparameter modifications may be necessary to break through this plateau. With modest changes presumably due to random fluctuations rather than major differences in learning approach or capabilities, DPG and A2C performed similarly. The hardest setting, pong, showed how difficult it was for these algorithms to understand complicated visual inputs and carry out long-term strategic planning as shown in Fig. 2. For example, DQN failed to learn an efficient strategy and settled to the least possible score, probably because of the sparse reward function. A larger replay memory would enable the network to form a more thorough grasp of the game dynamics, hence increasing memory capacity might be able to fix this. This conjecture finds validation in the research of [34], wherein successful learning outcomes were achieved with a significantly bigger memory capacity and longer training duration. With small gains that were within the standard deviation of run results, DPG and A2C both demonstrated minimal learning in pong, indicating that a substantial amount of extra training time would be needed to make noticeable improvements. However, this study emphasizes that DeepRL can handle challenging problems, but for the algorithms to function well, it usually needs a lot of processing power and a lot

[4] https://openai.com/research/openai-gym-beta

of training. The findings also highlight the difficult problem of striking a balance between the necessity of certain hyperparameter settings and the possibility of over-specializing the AI to a certain task context. Long-term hyperparameter tuning may result in excellent performance in a controlled experiment, but this does not guarantee generalizability or application in a variety of real-world or diverse contexts. This problem exemplifies bigger problems in AI research, where optimizing an algorithm for a particular set of conditions could unintentionally limit its applicability in other environments. The findings also highlight the practical ramifications of using AI in real-world applications, such robotics, where the implementation of high-capacity models that necessitate considerable training is limited by computing restrictions. These results highlight the continuous requirement for AI developments that can learn efficiently with reduced dependence on massive data inputs and processing capacity.

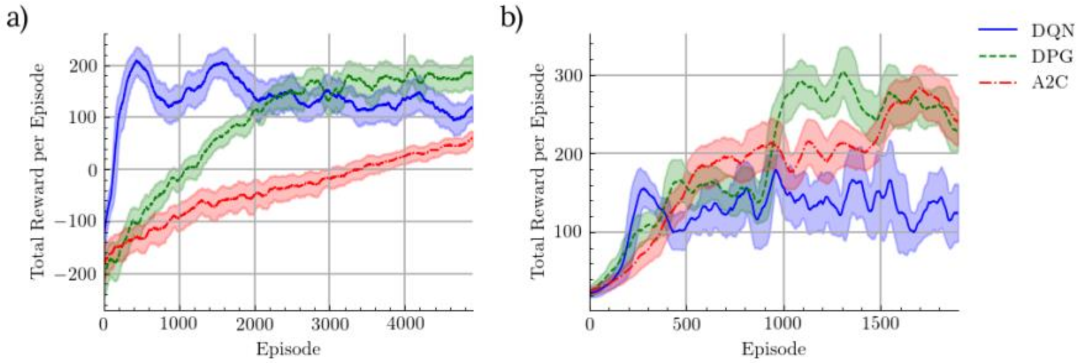

Fig. 1. Cart pole and lunar lander data displaying the running average of 100 episodes over ten samples. Between runs, the upper and lower lines show a single standard deviation limit. a) The total lunar lander incentive for every episode. b) The entire cart pole reward for each episode

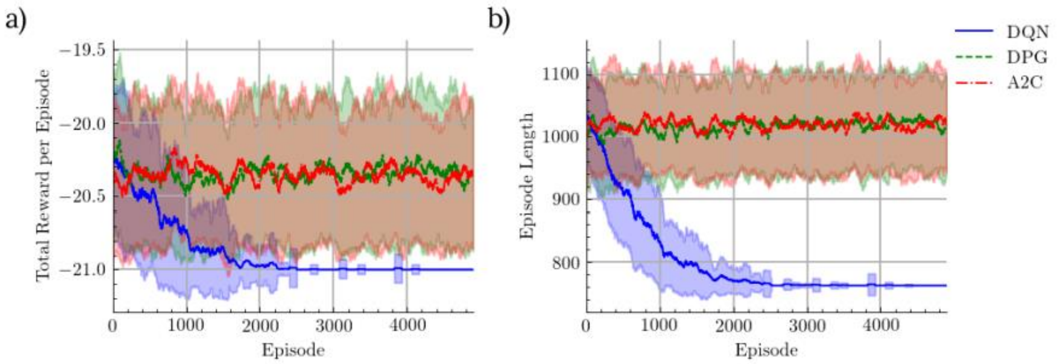

Fig. 2. The running average of 100 episodes over three samples is displayed in the pong results. One standard deviation limit between runs is indicated by the upper and lower lines. a) The overall prize for pong in every episode. b) The duration of each pong episode

5.1 Additional Experiments

The purpose of this study was to examine the common limits between DeepRL and classical conditioning, with a particular emphasis on robot navigation, task performance, and adaptability. According to the hypothesis, both approaches will face comparable difficulties when a robot needs to negotiate a maze in a partially accessible environment. The experimental design consisted of a robot walking through a maze with restricted sensory input, i.e., knowledge about the immediate eight surrounding grids, to mimic conditions similar to real-world scenarios when comprehensive information isn't always available as shown in Fig. 3. This configuration challenges the conventional Markov decision processes, which presuppose that past states don't directly affect future rewards. It is inspired by how human newborns gain object permanence, recognizing that items out of view still exist. Within the maze setting, the robot had three distinct navigation difficulties to fulfil. The first challenge was to find a way to a fixed endpoint from a fixed starting place. To evaluate the robot's capacity to react to dynamic changes in the environment, the second challenge involved changing the goal location between three specified spots, resulting in an increase in complexity. The robot's capacity to extrapolate from prior experiences and modify its pathfinding to suit novel situations was further tested in the third task, which changed the starting location while maintaining the goal as shown in Fig. 4. In this experiment, the robot was equipped with classical conditioning methods like

Associative Search Element (ASE) and the Actor-Critic version with Adaptive Critic Element (ASE-ACE), as well as algorithms like 2-layer DQN, DPG, and A2C as shown in Table 1. To avoid the algorithms merely memorizing pathways, each algorithm was adjusted via hyperparameter optimization carried out in distinct mazes that were not part of the main test mazes. From a fixed start to a fixed objective, the robots were able to navigate successfully, but when the target or start positions were changed, they encountered serious difficulties as shown in Fig. 5. Surprisingly every technique performed poorly on a task where the objective location was constantly shifting, suggesting a general lack of flexibility in responding to dynamic targets. This result emphasizes how difficult it is for DeepRL and classical conditioning to perform in situations where planning for possible future states and changes is just as important as storing memories. Furthermore, the experiment demonstrated that in AI systems, generalizability is more important than just task-specific optimization. When asked to adapt learned behaviors to novel and changing settings, robots performed well in controlled, constant environments but badly underwent changes as shown in Fig. 6. This problem highlights a critical area for additional AI research—improving learning algorithms' capacity to anticipate and dynamically adapt to new difficulties, rather than merely learning and following established procedures or techniques. In addition to laying the groundwork for the development of more resilient and adaptive AI systems that can function in a variety of unpredictably changing environments, this research advances our understanding of the basic limitations of the currently available AI learning frameworks. The results support the development of AI that can predict and strategically navigate future uncertainty in addition to responding to immediate inputs, mimicking the cognitive changes seen in newborn humans.

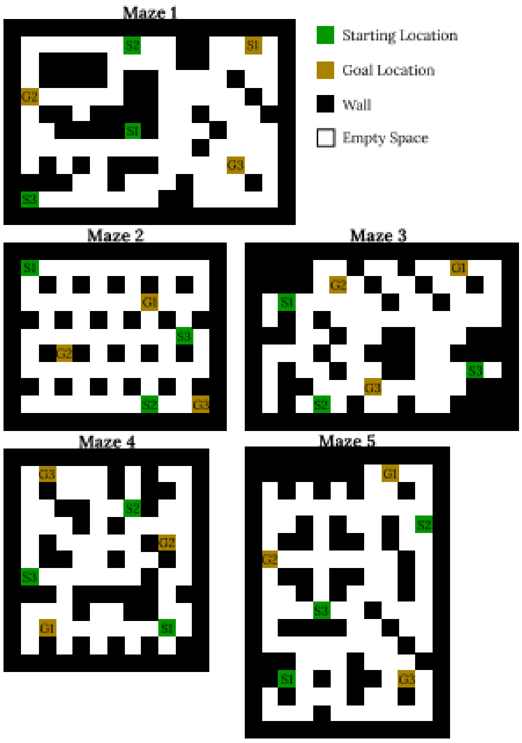

Fig. 3. Mazes employed in comparative analysis. The starting and goal locations are indicated by green and gold boxes, respectively. The starting locations are denoted by S1, S2, S3, and the goal locations are indicated by G1, G2, G3. The number designates the beginning and goal locations that are selected at random for various tests

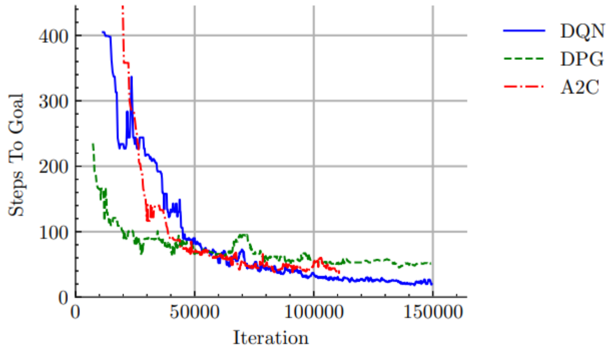

Fig. 4. The number of steps the robot takes in a timestep to locate the goal

Table 1. Outcomes of the maze trial

Method	Fixed Start with Fixed End	Fixed Start with Moving End	Moving Goal with Fixed Start	Total Across with All Tasks	
	Average Reward				Computation Times
Q-Learning (2-Layers)	3072 ± 386	230 ± 208	5021 ± 2647	8322 ± 2734	13.4 mins
Policy Gradient (2-Layers)	2158 ± 1801	43 ± 42	1513 ± 556	3714 ± 1990	3.3 mins
A2C (2-Layers)	1991 ± 1922	21 ± 61	1247 ± 1070	3259 ± 2769	3.4 mins
Q-Learning (1-Layer)	309 ± 286	76 ± 50	612 ± 213	997 ± 387	4.5 mins
Policy Gradient (1-Layer)	2315 ± 853	51 ± 53	907 ± 381	3273 ± 1145	2.1 mins
A2C (1-Layer)	1007 ± 740	40 ± 38	905 ± 318	1951 ± 795	2.1 mins
ASE	339 ± 334	63 ± 65	332 ± 280	734 ± 361	0.9 mins
ASE-ACE	546 ± 626	10 ± 28	13 ± 35	569 ± 662	2.2 mins
Random Actions	191 ± 26	137 ± 29	180 ± 25	508 ± 52	1.4 secs
Random Actions with Heuristic	318 ± 34	232 ± 33	309 ± 33	859 ± 62	1.2 secs

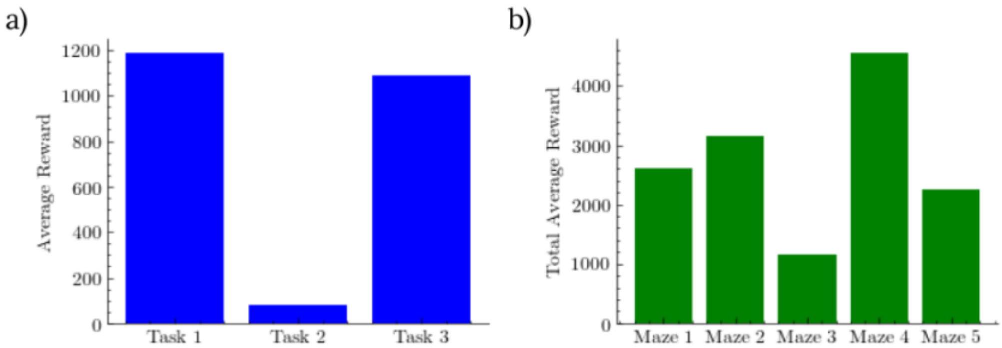

Fig. 5. a) The mean payout for every task using all available methods; b) The mean payout for every maze using all available ways

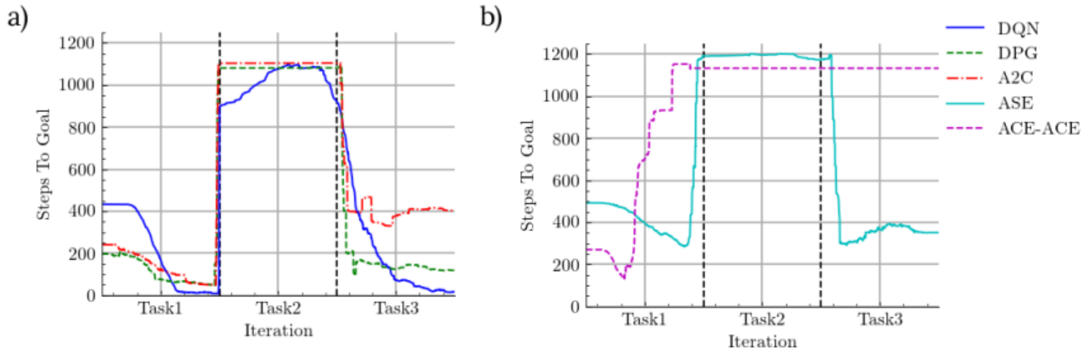

Fig. 6. The number of steps the robot takes, for each timestep and method, to locate the destination. Outcomes after ten runs on Maze 1. A running median filter with a window size of 100 objectives is applied to the graph. a) Deep learning techniques' effectiveness. b) The effectiveness of classical conditioning techniques

6. Conclusion and Future Works

Using the paradigm of classical conditioning and Markov decision processes, in particular, this study provided important insights into the capabilities and constraints of autonomous AI systems in robotic applications. In order to simulate real-world difficulties in robot navigation and adaptability, the study used a unique experimental setting consisting of computationally inexpensive activities inside a partially viewable maze. Robots were put through a range of challenging tasks in the studies, from travelling between fixed points to adjusting to dynamically changing goals. The results showed that although robots could perform static tasks, they were quite poor at situations requiring extensive planning and flexibility, like when targets moved randomly. These findings point to the need for more study into AI approaches that go beyond conventional Markov decision processes frameworks and classical conditioning techniques, especially ones that can dynamically adopt new strategies and unlearn unproductive behaviors. Creating AI systems [35] – [46] with the ability to independently plan activities and adapt taught behaviors in response to shifting environmental inputs may be one way to address this. To help these systems function better in a variety of uncertain situations, future research may look into improving the computing efficiency and generalization capacity of these systems.

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