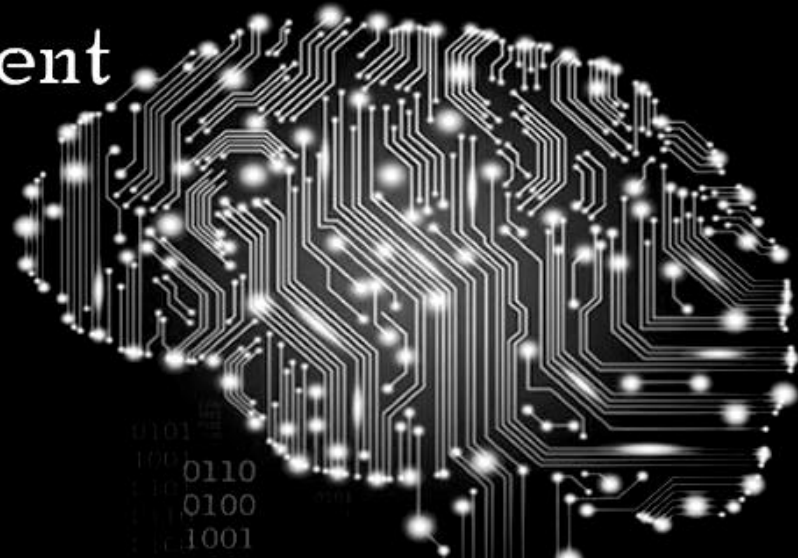


# AUTONOMOUS MOBILE ROBOT NAVIGATION USING REINFORCEMENT LEARNING

Reinforcement  
Learning



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# INTRODUCTION

- Autonomous mobile robots are the robots that have autonomous decision making capabilities in order to navigate in state-space.
- However, they face lots of challenges like lack of knowledge of it's position, imprecise sensor data and inability to replicate performance in new environment.
- To make the robot know it's position we have SLAM techniques. To address imprecise sensor data, we have Kalman filtering but performance replication is still a major issue.
- This is where AI/ML based models greatly contribute to robotics.

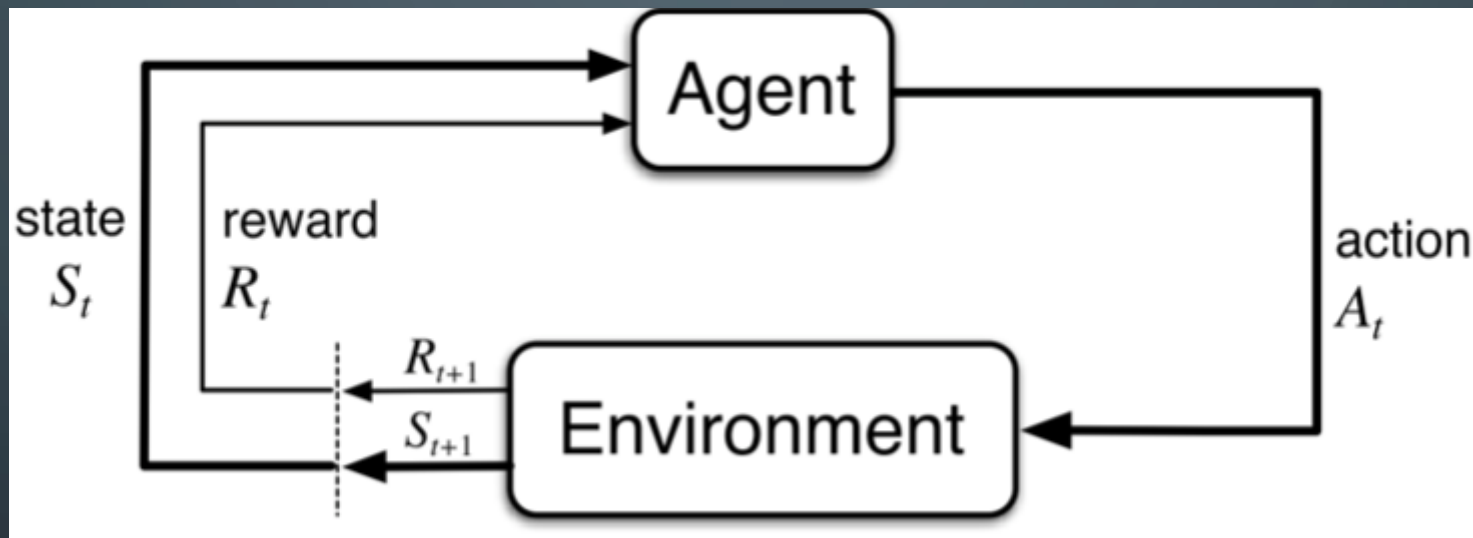
# WHAT IS LEARNING AND WHY DO WE NEED IT?

- AI is an umbrella that consists of various techniques like ML, CV, NLP, Evolutionary algorithms, etc...
- Machine learning is defined as the ability of a machine to learn, without explicitly being programmed.
- Machine learning can be classified into 3 topics: Supervised Learning, Unsupervised learning and Reinforcement learning.
- In conventional control algorithms there is no scope for improvement. The control law is explicitly stated and can't adapt to new environments

# REINFORCEMENT LEARNING

- Instead of explicit coding of control laws, coding the control law via RL method makes the robot to “learn from experience”.
- This is analogous to how a baby learns to walk by falling down and learning.
- A mathematical reward is assigned for every desired task (distance traversed without collision) and a punishment is assigned for every undesirable task (collision with objects)
- The robot “learns” by trying to maximize its reward and minimize punishment.
- RL is an example of a Markov Decision Process.

# RL BLOCK DIAGRAM



- State is given by the sensors, while action (forward, reverse) is performed by actuator.

# RL TYPES

- RL has 3 types: Value based (Q learning), Policy based (Actor Critic) & model based.
- Value based algorithms are optimized to get maximum value (Q value).

$$v_{\pi}(s) = \mathbb{E}_{\pi} [ \underbrace{R_{t+1}}_{\text{Expected}} + \underbrace{\gamma R_{t+2}}_{\text{Reward discounted}} + \gamma^2 R_{t+3} + \dots \mid \underbrace{S_t = s}_{\text{Given that state}} ]$$

- Policy based iterations are optimized to get the best possible policy (control law) based on probability distribution of next state.

$$\text{Stochastic policy: } \pi(a|s) = \mathbb{P}[A_t = a | S_t = s]$$

- Model based approaches require knowledge of existing environment and try to optimize it.
- Exploration vs Exploitation.

# WORK DONE IN THE LAST MONTH

- Identifying the problem statement and planning a sequential set of actions in order to converge to a solution.
- Thorough literature survey, understanding previous research papers and going through the Reinforcement learning textbook by Sutton and Barto.
- Understanding the mathematics and working of Q-Learning algorithm.
- Converting Q-Learning Pseudocode to MATLAB code.
- Debugging the code and evaluating its performance in MATLAB.
- Visualizing the performance and result of the Q-learning algorithm in MATLAB by implementing a 2D simulation framework.

# Q- LEARNING ALGORITHM PSEUDOCODE

*Estimate the start state*

*While state  $\neq$  terminal (exit of the maze)*

*Choose an action based on e-greedy method (exploration and exploitation approach)*

*Execute the action (forward, right or left by enabling both motors, left motor or right motor, respectively)*

*Measure output voltage of the proximity sensors*

*Update the state vector and its type (health/subhealth)*

*Check if there is an emergency condition (any of the sensors has a distance shorter than the minimum allowed for subhealth state)*

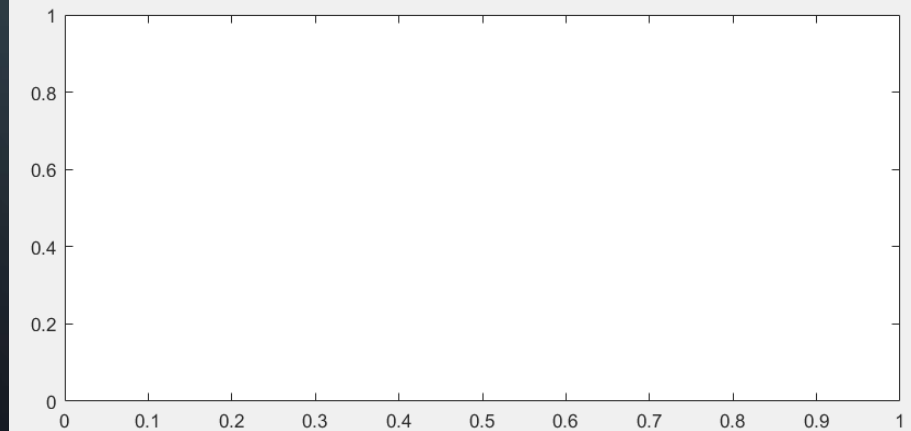
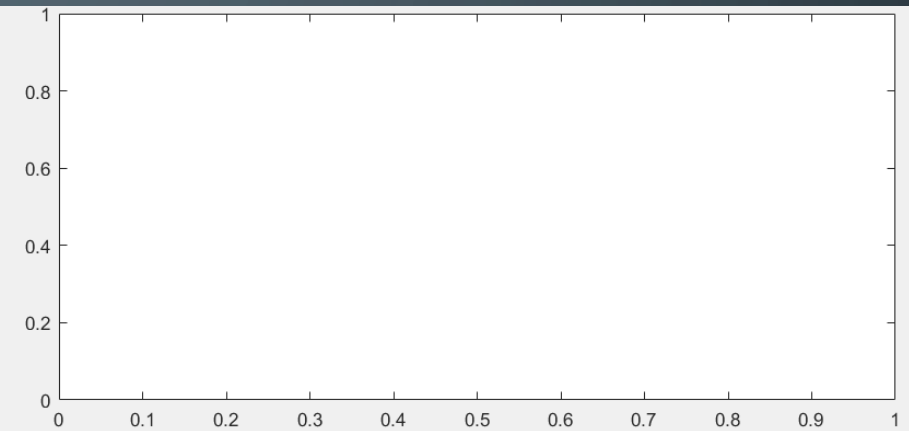
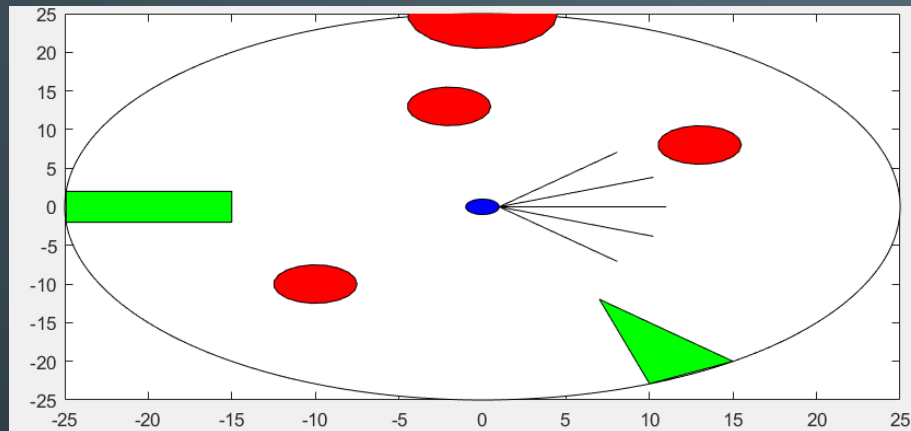
*Obtained rewards based on prior state and executed action*

*Update the action value function  $Q$*



# 2D SIMULATION ANALYSIS

BEFORE:



Informasjon					
Trials:	0	Steps:	0	Total reward:	0.00
l_zone:	2	r_zone:	2	Action:	left
l_sector:	2	r_sector:	2	Crash:	0

Start

Pause

Maxsteps: 600

Upload

Save

gamma: 0.9000

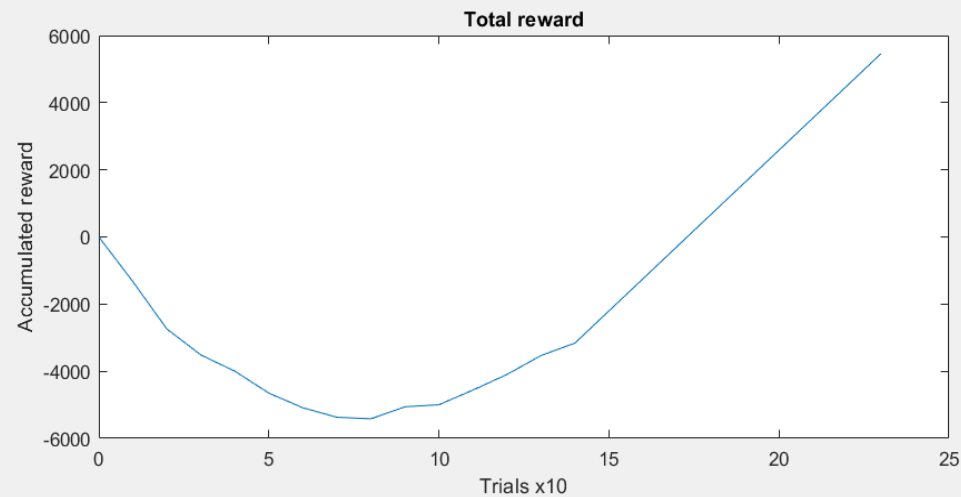
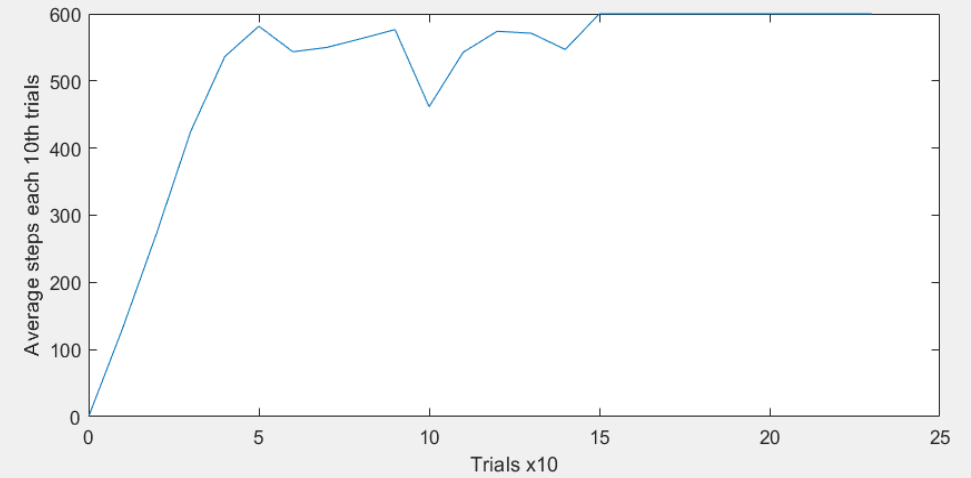
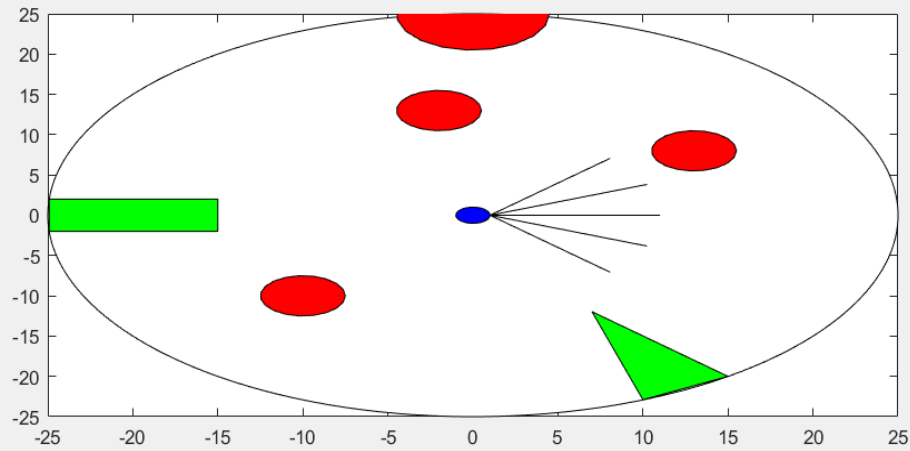
E 9500

Reset

T(Soft-max): 24

# 2D SIMULATION ANALYSIS

AFTER:



Informasjon			
Trials:	232	Steps:	600
l_zone:	1	r_zone:	2
l_sector:	1	r_sector:	2
		Total reward:	95.80
		Action:	forward
		Crash:	42

Start

Pause

Maxsteps: 600

Upload

Save

gamma: 0.9000

E: 9500

T(Soft-max): 24

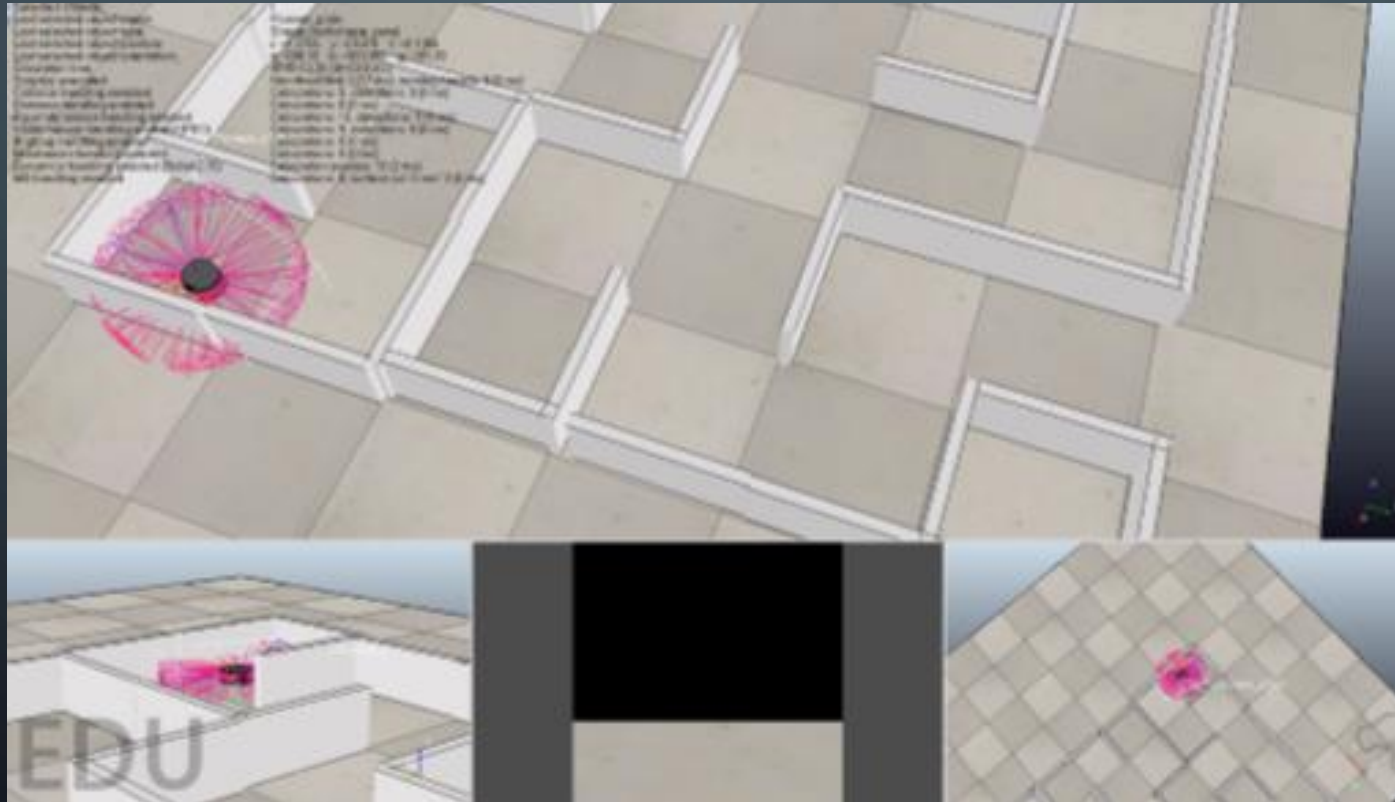
Reset

# PLANNED WORK OVER THE NEXT 2 MONTHS

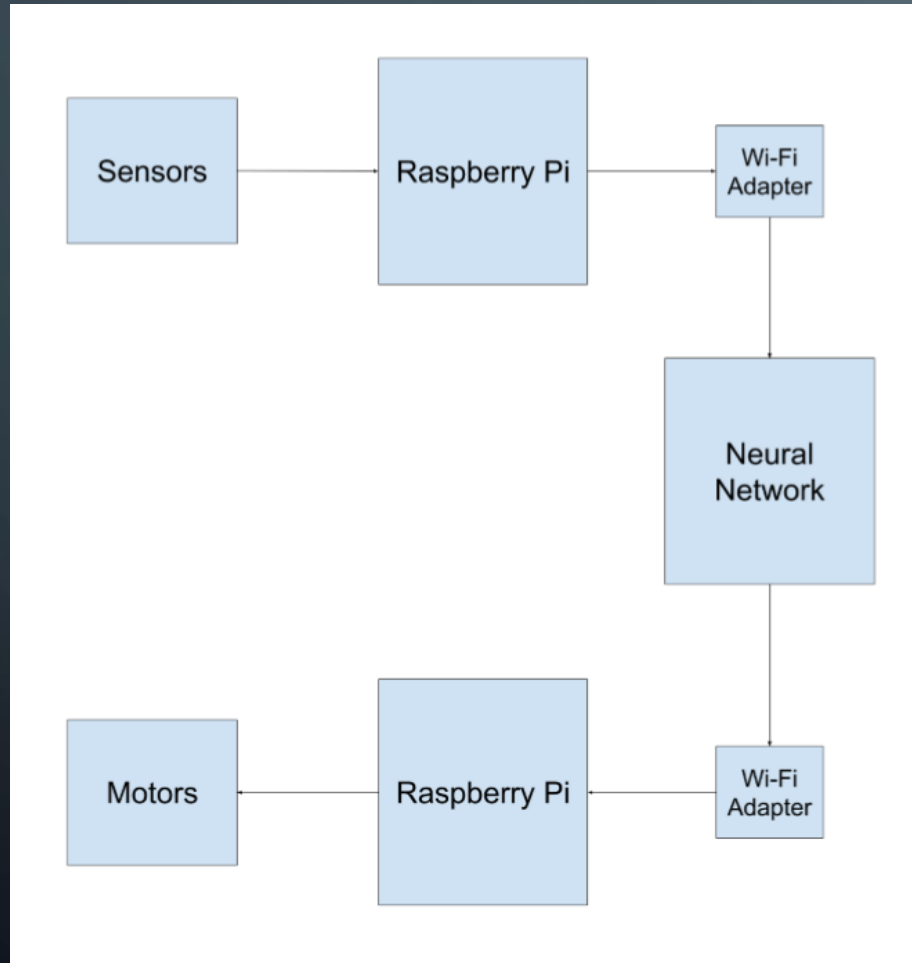
- 2D simulations are used to analyze and visualize the performance of the algorithm. We need 3D simulations in order to replicate the real-world performance of the algorithm.
- 3D Simulation using Virtual Robot Experimentation Platform (V-REP) by interfacing MATLAB.
- Testing the “learning ability” by simulating in a new environment.
- Explore different algorithms like Actor Critic, SARSA & compare performance.
- After 3D simulation, implementing this algorithm in a physical robot to measure real-world performance by using Rpi/Arduino for motor control and interfacing it with MATLAB and V-REP.
- Finally, documenting all the work done in the form of a research paper.

# V-REP ENVIRONMENT

- Allows interfacing of MATLAB, RPi and Arduino and replicates real-world performance. Artificial environments can be created in it and tested.



# BLOCK DIAGRAM FOR PHYSICAL IMPLEMENTATION



- RL is computationally intensive, so an on board Microcontroller cant compute the algorithm.
- So, we'll be interfacing RPi/Arduino with MATLAB.
- MATLAB in the laptop will run the RL algorithm and send control signals to RPi/Arduino, which will act exclusively as a motor controller.

Thank  
you