Enhanced mobile robot navigation using TD3 and DQN

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Introduction

This project focuses on the implementation of deep reinforcement learning algorithms on a mobile robot to navigate a given environment with obstacles using two algorithms: TD3 and DQN.

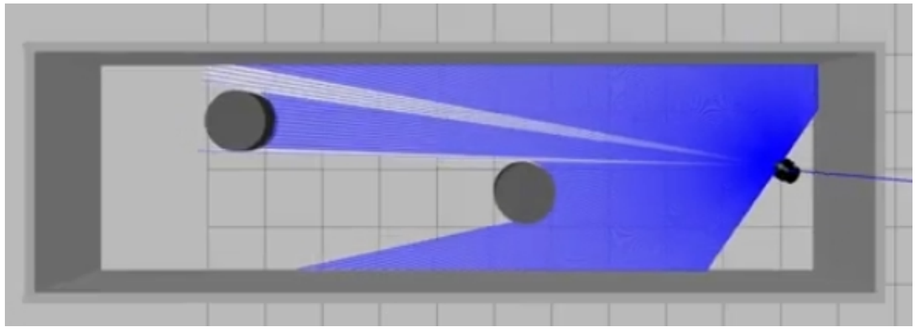
Optimized hyper-parameters to improve the convergence of Q-values.

Results are compared for two architectures:

- Shallow Neural Network
- Deep Neural Network

Tools Used

- ROS2 Humble
- Gazebo
- RViz
- Velodyne LiDAR



Gazebo Environment with LiDAR Rays on Mobile Robot

Twin Delayed Deep Deterministic Policy Gradient (TD3)

- Combines aspects of DDPG with improvements to address function approximation errors
- Actor-Critic Architecture
  - Actor network optimizes the policy.
  - Critic network evaluates action-value pairs.
- Training: Utilizes experience replay for learning from past experiences.
- Suited for environments with continuous action spaces
- Application: Used in robotic control, autonomous driving, and other applications requiring precise continuous control.

Algorithm 1 TD3

1 Initialize critic networks Q_{θ_1}, Q_{θ_2}, and actor network π_ϕ with random parameters θ_1, θ_2, ϕ
Initialize target networks $\theta'_1 \leftarrow \theta_1$, $\theta'_2 \leftarrow \theta_2$, $\phi' \leftarrow \phi$

2 Initialize replay buffer $\mathcal{B}$

for $t = 1$ **to** T **do**

3 Select action with exploration noise $a \sim \pi_\phi(s) + \epsilon$, $\epsilon \sim \mathcal{N}(0, \sigma)$ and observe reward r and new state s'

4 Store transition tuple (s, a, r, s') in $\mathcal{B}$

5 Sample mini-batch of N transitions (s, a, r, s') from $\mathcal{B}$
$\tilde{a} \leftarrow \pi_{\phi'}(s') + \epsilon, \quad \epsilon \sim \text{clip}(\mathcal{N}(0, \tilde{\sigma}), -c, c)$
$y \leftarrow r + \gamma \min_{i=1,2} Q_{\theta'_i}(s', \tilde{a})$
Update critics $\theta_i \leftarrow \text{argmin}_{\theta_i} N^{-1} \sum (y - Q_{\theta_i}(s, a))^2$

6 **if** t mod d **then**
Update ϕ by the deterministic policy gradient:
$\nabla_\phi J(\phi) = N^{-1} \sum \nabla_a Q_{\theta_1}(s, a)|_{a=\pi_\phi(s)} \nabla_\phi \pi_\phi(s)$

7 Update target networks:
$\theta'_i \leftarrow \tau\theta_i + (1 - \tau)\theta'_i$
$\phi' \leftarrow \tau\phi + (1 - \tau)\phi'$

end if

end for

https://towardsdatascience.com/td3-learning-to-run-with-ai-40dfc512f93

Deep Q-Learning (DQN)

- Reinforcement learning algorithm combining Q-learning with deep neural networks.
- Training:
  - Employs experience replay, a technique that stores and randomly samples past experiences to break temporal correlations, enhancing learning stability.
- To stabilize training, DQN uses two sets of networks—one for determining actions (policy network) and another for evaluating Q-values (target network).
- Application: Effective in playing video games, robotics, and other domains requiring decision-making in large state spaces.

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Initialize target networks $\theta'_1 \leftarrow \theta_1$, $\theta'_2 \leftarrow \theta_2$, $\phi' \leftarrow \phi$

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7 Update target networks:
$\theta'_i \leftarrow \tau\theta_i + (1 - \tau)\theta'_i$
$\phi' \leftarrow \tau\phi + (1 - \tau)\phi'$

end if

end for

Workflow

-TD3

- Created Gazebo world and deployed mobile robot
- Implemented the algorithm in a custom-made environment
- Addition of an extra layer of the neural network
- Using ROS Odometry information to calculate current position
- Comprehensive analysis of Shallow and Deep Neural Network to evaluate the performance using:
  -Average Q-values
  -Maximum Q-value
  -Network Loss

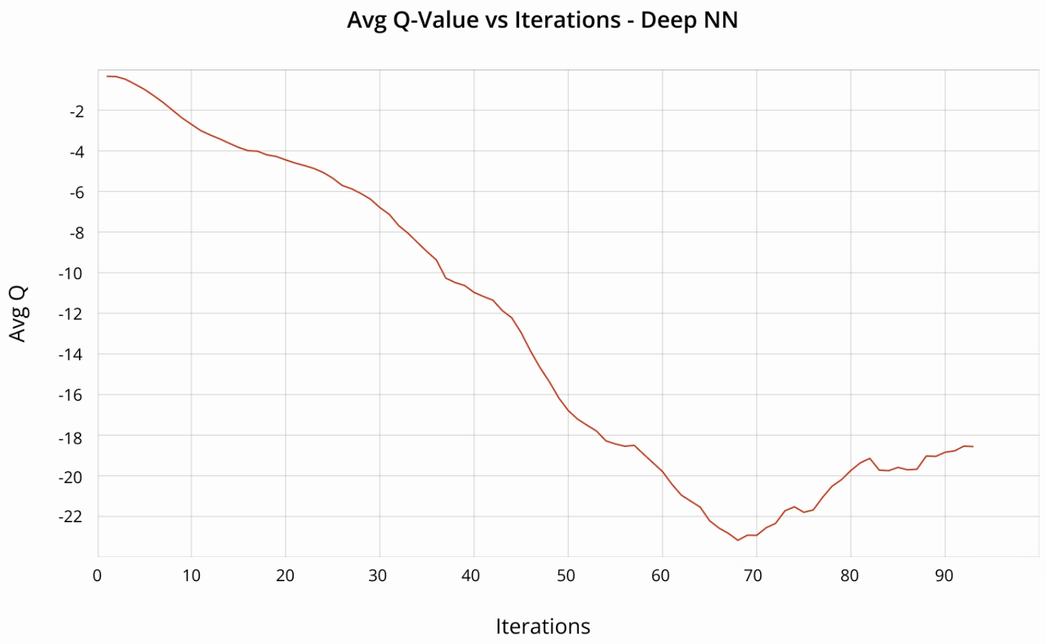
-DQN

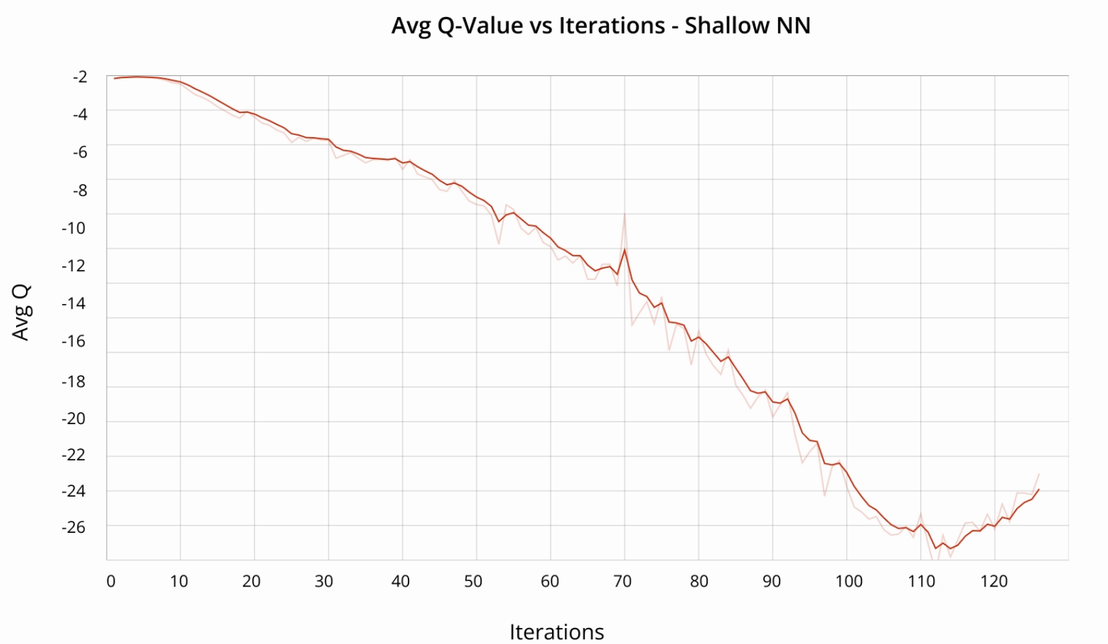
- Implementation of DQN algorithm in code to represent the maximum Q-values obtained.

Training Parameters

- Coefficient for updating the target network: 0.005
- Discount Factor: 0.99
- Noise Clip Threshold: 0.5
- Noise for exploration: 0.2
- Batch size: 100
- Buffer size: 1e6
- Epoch: 1
- Maximum Timesteps: 3e6
- Maximum episodes: 300
- Optimizer: Adam
- Evaluation frequency: 5000
- Evaluation Episodes: 10
- Training time: 45 minutes

Results

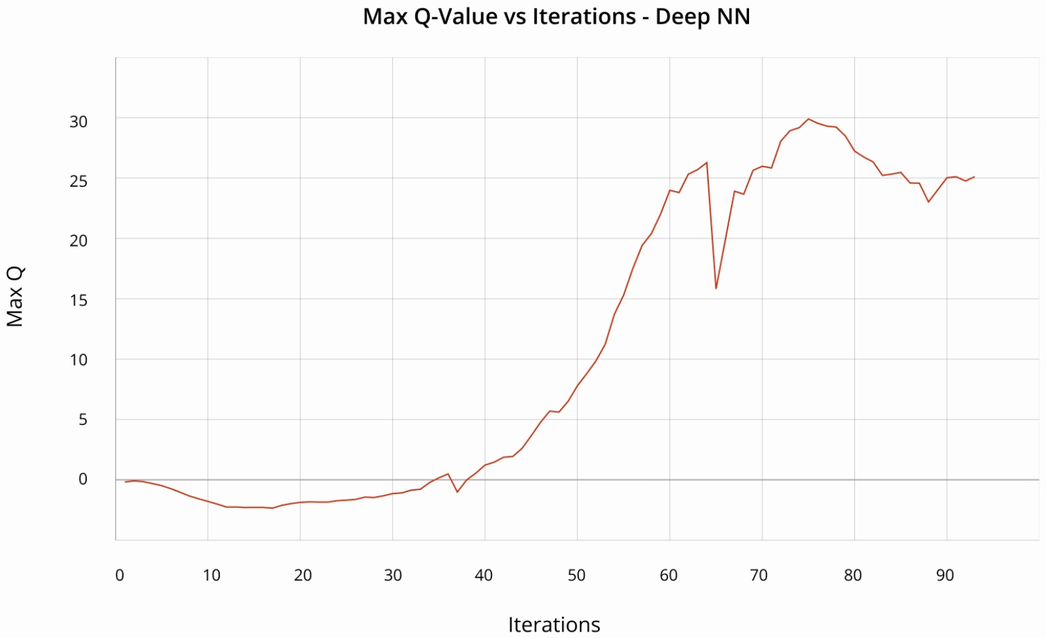


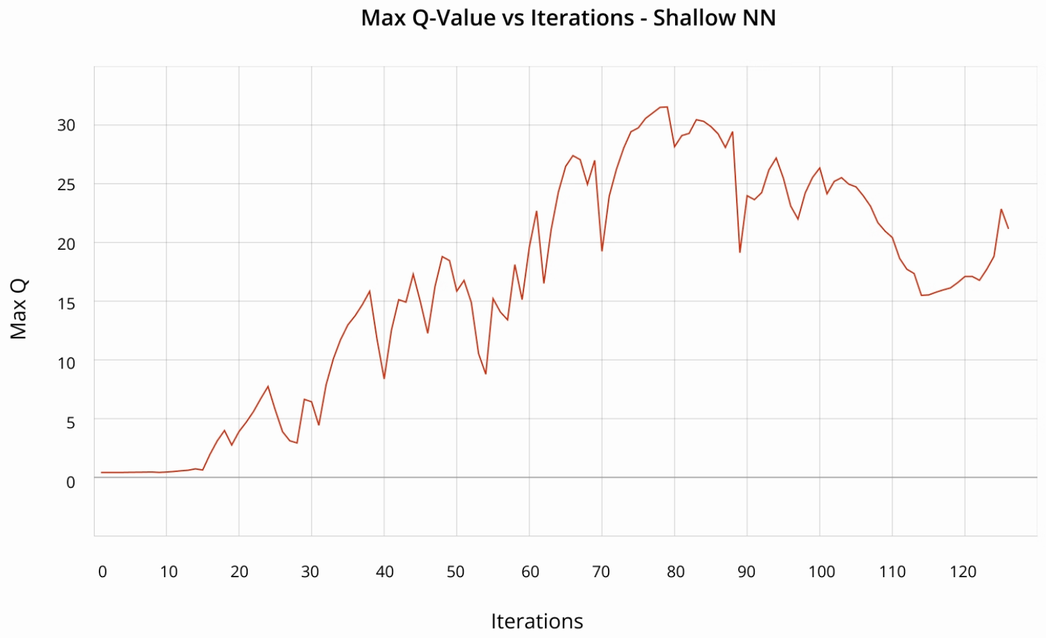


- More faster reduction in deep neural network
- Less Iterations
- Computationally Expensive

Avg Q-Value

Results

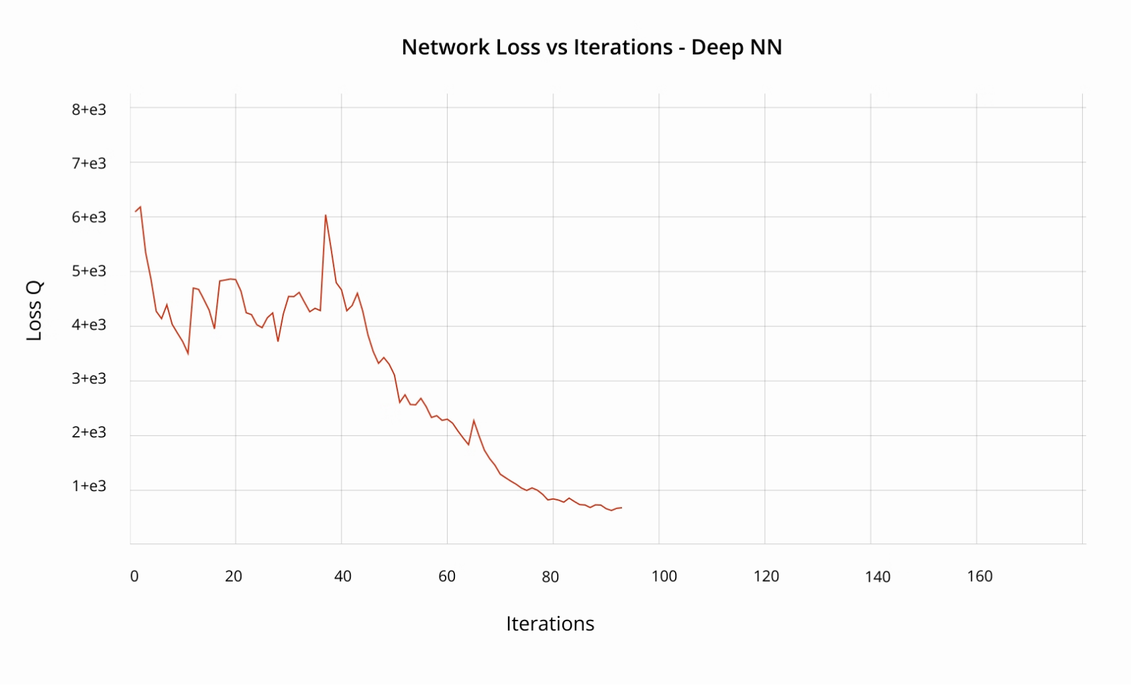


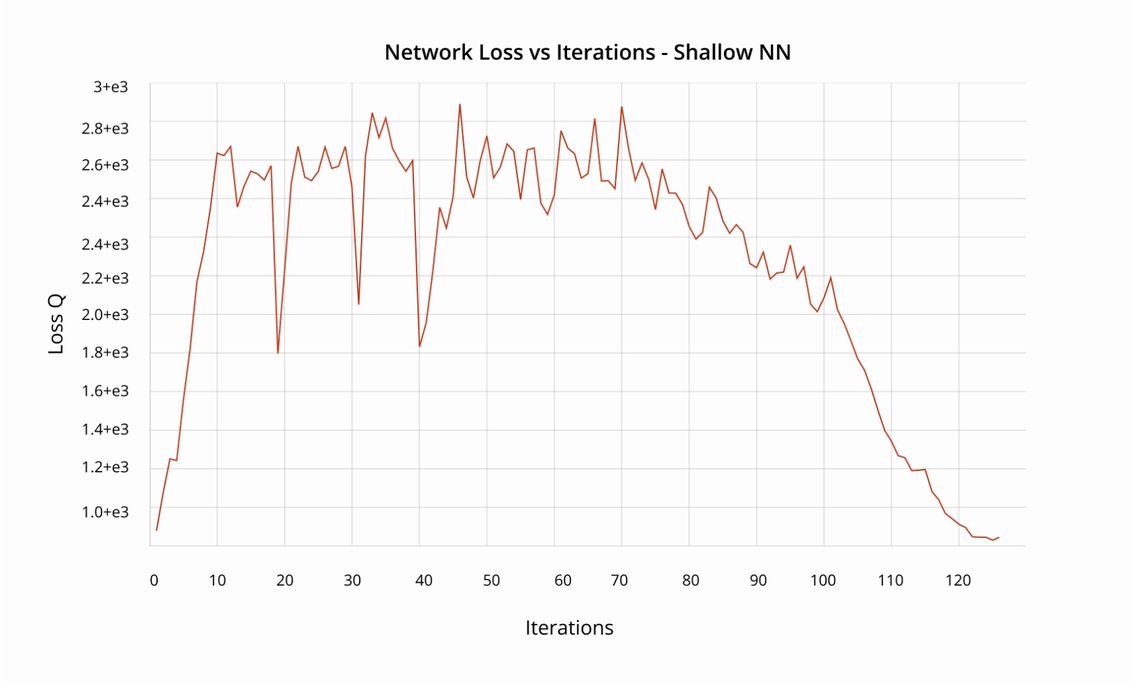


- Stable change in q values
- Less Iterations

Max Q-Value

Results

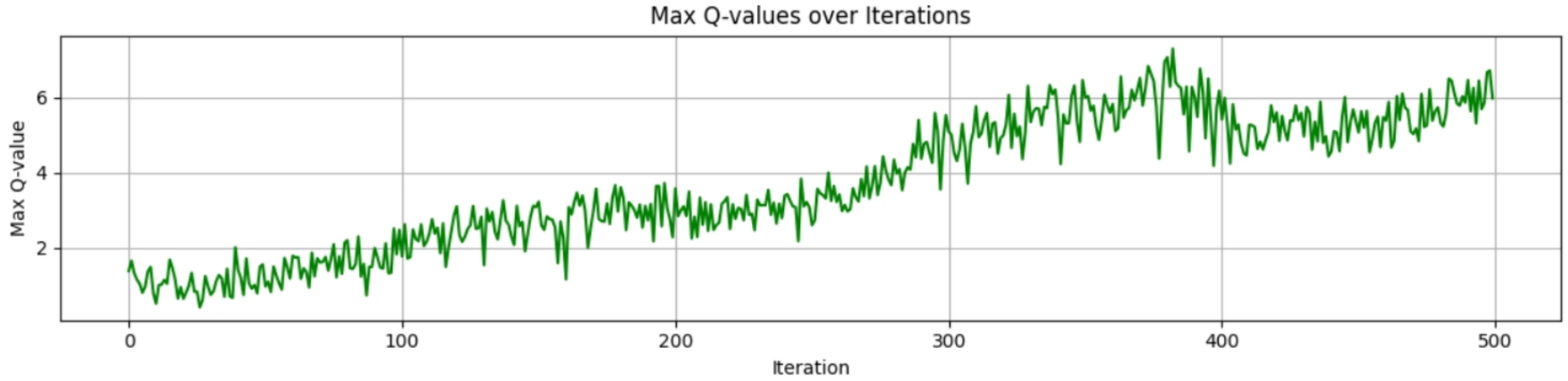




- More faster reduction in network loss
- Higher initial loss

Q - Loss

Results



Basic DQN

Demo

Training & Validation

https://drive.google.com/file/d/1czt7jeloPETLZ584lH3S5WX08z9aTNkd/view?usp=drive_link

Testing

https://drive.google.com/file/d/1czt7jeloPETLZ584lH3S5WX08z9aTNkd/view?usp=drive_link

Improvements

- Limiting the state-action generation to a constrained space instead of learning multiple state-action pair
- Increase in the number of iteration to better train the model
- Accuracy can be increased with increasing epochs and episodes

- Stabilizing the robot and remove wobbling while braking

Demo

References

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