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"Self Driving Car Using Deep Q - Learning"

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Abstract

An autonomous vehicle model using Deep Q-learning on simulator is planned. Autonomous cars are one of the greatest growing fields in upcoming decade as the certainly developing hardware and software technologies to fully independent driving ability without human interference. Autonomous vehicles are destined to be the cornerstone in shaping the future of mankind. Deep Learning(DL) has shown to achieve remarkable performance and accuracy in various insight and tasks in comparison to other methods. The key these key functions aspects for these remarkable results are their capability to learn millions of parameters using a huge volume of labeled data. Deep Q- Networks (DQN), a reinforcement Learning algorithm that accomplished human-level performance across various fields.

Keyword*: Artificial Intelligence, Machine Learning, Deep Q-Learning, Reinforcement Learning, Neural Networks.*

Introduction:

Autonomous cars have been one of the most important prospects for AI research, it would be the extreme high-tech revolution of the near future. Car will run in a virtual environment. The Car is designed using KIVY library. Car has 3 sensors that take if from 3 directions. Deep Q-Learning is used to change the direction of the car when it encounters a obstacle. Obstacle here is considered to be sand. The car slows down as it moves through the sand. The RL intermediaries incrementally update their parameters (value function or model) while they observe a stream experience. In their simplest form, they remove incoming data immediately, after a single update. According the actions taken by the car the it gets positive or negative reward. The closer the car gets to the destination it gets positive and vice versa.

Related work:

To build AI which will be embedded into the self-driving car that reaches from the given starting point to the destination. In our case the Right bottom corner is considered to be the starting point and the top left corner of the screen is considered to be the destination. Truong-Dong Do[2] put forth an autonomous vehicle platform based on AI technology: Start to finish deep learning based instantaneous control. Tom Schaul [3] defined how experience replay lets RL agents recollect and reuse experiences from the historical data. In previous work, experience transitions were uniformly sampled from play memory also used for prioritized experience replay in DQN, a RL algorithm that accomplished humanoid performance across many Atari games. DQN with prioritized experience replay achieves a new state of-the-art, outperforming DQN with consistent replay on 41/49 games. The Q-network parameters are updated with an experience replay and a second target Q network is used to relieve the problems of local optima and instability. Model training and fine-tuning, refinement of proposed

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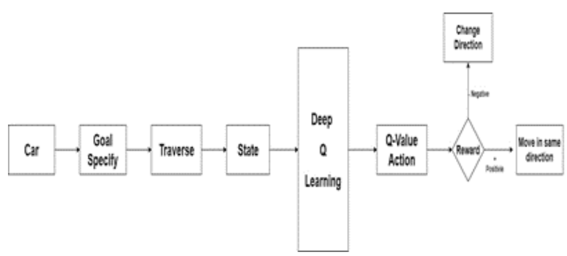
methodologies, and performance evaluation of deep learning approaches remain topics of our further studies. Matt Vitelli [5] This plan has verified the efficiency of circumnavigating autonomous vehicles using RL approaches. We have demonstrated that DQNs can be an operative means of controlling an automobile directly from higher dimensionality sensual inputs, and we used grouping of CNN and RNN to accomplish this.

Although presently it seems as though, lower dimensionality discrete state-space agent is able to further strongly control a car as compared to a more complex DQN agent, being certain that our work could be developed and used in many ways, we developed this model . Specifically, it would be great to find an improved alternate option for redefining our reward function that still keeps intact the cautious balance between maximizing speed while guaranteeing precision and the stability of the car . Correspondingly, it would be interesting to take a broad view of our work to continuous action spaces. In spite of these boundaries, that our agents were able to effectively govern a car without any explicit interference of the car's fundamental dynamic forces.

System Modules:
Our System mainly contains three modules Car, Obstacles and Environment.

System Architecture:
In the system, we design and develop a car which is imbedded with AI such that it travels from a given starting point to the specified destination by using the deep Q-Learning mathematical model. Whenever, an obstacle is detected using the deep Q-learning principles it avoids that obstacle. Based on the action of the car the rewards are given.



Deep Q-Learning (DQN):

What is Deep Q-Learning?
Q-Learning is a basic form of Reinforcement learning algorithm. Q-learning algorithm uses Q-values to improve the efficiency or accuracy of the system under consideration. It is the learning process where the algorithm learns overtime to behave optimally in an environment. It interacts with the given environment to provide a accurate system. Deep learning is a part of machine learning which is completely built on Artificial Neural networks. As it works like a human brain i.e. it mimics the human brain it does not need to be programmed explicitly. The process of Q-learning creates the exact matrix for the system to work on but it is limited only to the smaller environments. Deep Q-learning considers these Q-values and then the neural networks work on them to approximate these values. The basic working of deep Q learning is that the initial step is fed into the neural networks to get the approximate Q value. There may be many such Q-values for the same state. The best value is selected from the list of values.

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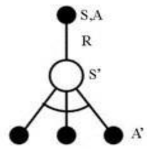
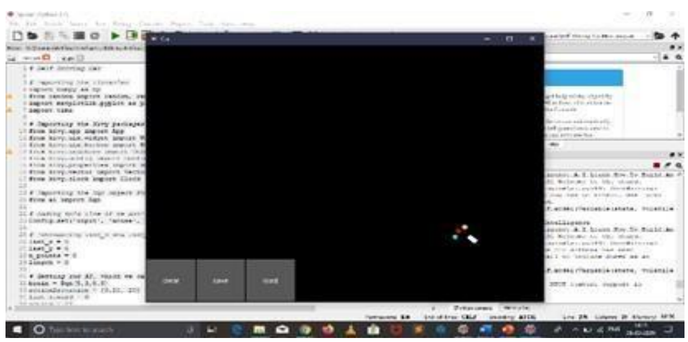
Mathematical Model:



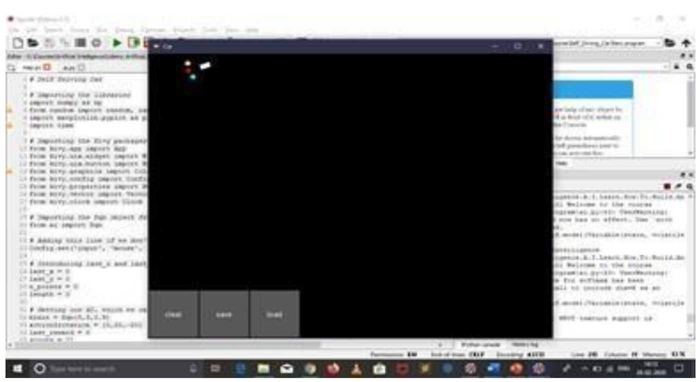
$$Q(S,A) \leftarrow Q(S,A) + \alpha \left(R + \gamma \max_{a'} Q(S',a') - Q(S,A) \right)$$

Conclusion:

This scheme has illustrated the efficiency of navigating self-driving vehicle by means of RL procedures. We have publicized that DQNs can be an efficient means of controlling a car directly from higher dimensional sensory inputs, and we used an innovative mixture of CNN and RNN to achieve this stability. Although presently it seems as though, lower dimensionality discrete state-space agent is able to further strongly control a car as compared to a more compound DQN agent, being certain that our work could be developed and used in numerous ways, we developed this model. It would be nice to find a well alternative of defining our reward function the careful balance between maximizing speed while guaranteeing the accuracy. Specifically, it would be great to find an improved alternate option for redefining our reward function that still keeps intact the cautious balance between maximizing speed while guaranteeing accuracy and the stability of the car. Despite these limits, we are still proud of the work nthat our agents were able to completely control a car without any obvious notion of the car. The Car after embedding the AI moves from the starting that still maintains point to destination avoiding the obstacles and reaching the destination.



1) Starting Point



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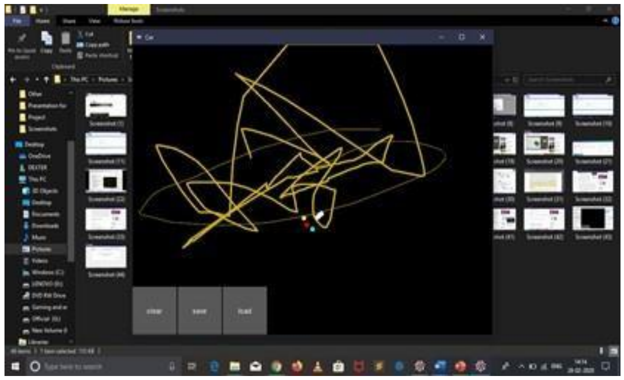
2) Destination Point



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