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# Autonomous Vehicle Using Various Machine Learning Algorithms

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## ABSTRACT

Today and possibly for a long time to come, the full driving task is too complex an activity to be fully formalized as a sensing-acting robotics system that can be explicitly solved through model based and learning-based approaches in order to achieve full unconstrained vehicles autonomy. Vehicle control, mapping, scene perception, trajectory optimization, and higher-level planning decisions are open challenges for autonomous vehicle development. This is especially true for real-world operation where the margin of allowable error is extremely small and the number of edge-cases is extremely large. Human beings will remain an integral part of monitoring the AI system as it performs anywhere from just over 0% to just under 100% of the driving until we solved these problems. We are continually developing new methods for analysis of the massive-scale dataset collected from various vehicle owners. Many recorded data has various messages, and high-definition video streams of the driver face, the driver cabin, the forward roadway, and the instrument cluster. The study is on-going and growing. Till date, we have 110 participants, 11,945 days of participation, 89,405,807 miles, and 10.9 billion video frames. Here we presents the design of the study, the data collection hardware, the processing of the data, and the computer vision algorithms currently being used to extract actionable knowledge from the data.

**Keywords:** Self-driving car, Regression, Clustering, Decision Matrix, Pattern Recognition, Reinforcement Learning, Markov Decision Process, Q-Learning

## I. INTRODUCTION

Human drivers are poor is shown in our popular culture. [1], [2] This idea is often dramatized, there is some truth to it in that we are sometimes distracted, drowsy, drunk ,drugged, and irrational decision makers.[3] It is not easy to design and build a perception-control system that drives better than the average human drivers.6 of the 11 autonomous vehicles successfully navigated an urban environment to reach the finish line, with the first place finisher traveling at an average speed of 15 mph in 2007 DARPA Urban Challenge [4] which was a landmarks in autonomous vehicle driving. After the success of this competition many believe that fully autonomous driving task is solved and few remaining messy details to be resolved by automakers as part of delivering a commercial product. Even today the problems of vehicle control, mapping, scene perception, trajectory optimization, and higher-level planning decisions associated with self-driving vehicle development remain full of open challenges that have yet to be fully solved by systems incorporated into a production platforms for even a restricted operational space. Human is responsible for taking control during periods where the AI system is unable to safely proceed [5], [6]. Being human, we take granted of word robotics and it's intelligence, which is required to successfully attain enough situation awareness and understanding [8] to navigate through a world full of predictably irrational human beings moving in cars, on bikes, and on foot. It may require decades to see majority vehicles autonomous on the road. And in all this human is a critical decision maker whether he drive or supervise AI for driving.

NDS is a type of study that collects video, audio, vehicle telemetry, and other sensor data that captures various aspects of driving over a longer periods of time, ranging from multiple days to multiple months and even years. NDS stands for Naturalistic Driving Study. The term NDS is applied to studies in which data are acquired under conditions that closely align with the natural conditions under which drivers typically drive "in the wild." Registered vehicle is instrumented and to continue using their vehicle as they ordinarily would and data is collected throughout periods of use. The purpose of this is to provide a record of natural behaviour that is unaffected by the measurement process as possible. Road experiments are conducted using these data and asks the driver to use the technology in given road at specific time.

To be fall on "fully autonomous" category, a car must be able to navigate between destinations without any intervention from a human driver. Self-driving cars aim is to increase safety by eliminating human errors from driving situations and other human silly mistakes.

Fully autonomous vehicle will be controlled by an onboard computer, using a combination of sensing systems, such as LiDAR, radar, and cameras, that perceive the roadways and surrounding environments. Autonomous systems are designed to drive cars safely while eliminating human failings such as cell phone distractions or drowsy inattention.

## II. WHICH ALGORITHM TO USE?

The application based on machine learning includes the driver's speech and gesture recognition and language translation. An unsupervised learning and a supervised learning are the algorithms from which application learn.

Training dataset is used by supervised learning algorithms to learn and they continue to learn till they get to the level of confidence they aspire for (the minimization of the probability of error). The supervised algorithms can be categorized into regression, classification and anomaly detection or dimension reduction.

The Unsupervised learning algorithms try to derive value from the available data. Within the available data, this algorithm develops a relation in order to detect the patterns or divides the data set into subgroups depending on the level of similarity between them. The Unsupervised algorithms can be largely categorized into association rule learning and clustering.

The reinforcement learning algorithms are another set of machine learning algorithms which fall between unsupervised and supervised learning. For each training, there is a target label in supervised learning algorithms; there are no labels at all in unsupervised learning algorithms; the reinforcement learning algorithms, consists of time-delayed and sparse labels – the future rewards.
In self-driving car , one of the major tasks of a machine learning algorithm is continuous rendering of surrounding environment and forecasting the changes that are possible to these surroundings. These tasks are classified into 4 sub-tasks:

- The detection of an Object

- Recognition of object classification
- The Object Localization and Prediction of Movement

## III. TYPES OF ALGORITHMS

### A. Regression Algorithms

Regression algorithm is good at predicting events. The Regression algorithm Analysis evaluates the relation between 2 or more variables and collate the effects of variables on distinct scales and are driven mostly by 3 metrics:

1. The shape of regression line.
2. The type of dependent variables.
3. The number of independent variables.

To develop an image-based model for feature selection and prediction all the images play a significant role. Without images we cannot obtained a features to train and test.

The renewal of the environment is hold by regression algorithms to create a statistical model of relation between the given object's position in an image and that image. By allowing the image sampling, provides fast online detection and can be learned offline which can be extended furthermore to other objects without the requirement of extensive human modelling. Algorithm returned the object's position as the online stage's output and a trust on the object's presence.

Regression can also be utilized for short prediction, long learning. Decision forest regression, neural network regression and Bayesian regression can be utilized in self-driving car.

### B. Decision Matrix Algorithms

This algorithm systematically analyses, identifies and rates the performance of relationships between the sets of information and values. These algorithms are majorly utilized for decision making. Whether a car needs to brake or take a left turn is based on the level of confidence these algorithms have on recognition, classification and prediction of the next movement of objects. Models composed of various decision made by decision matrix algorithms which is trained independently in some way, these predictions are combined to make the overall prediction, while decreasing the possibility of errors in decision making.

### C. Support Vector Machines (SVM)

Support Vector Machines (SVM) are dependent on the decision planes concept that define the decision boundaries. A decision plane divides the different sets of memberships with its unique features. A schematic example is illustrated below.

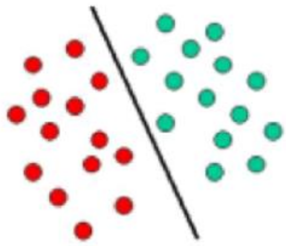

**Figure 1.** SVM[9]

In this figure, the objects belong to either RED or GREEN class. A boundary line separates the RED and GREEN objects. Any new object that falls to the left is labelled as RED and it is labelled as GREEN if it falls to the right.

### D. Clustering Algorithms

There are many times when the images acquired by the system are not clear and it becomes difficult to locate and detect objects. There may be a possibility of classification algorithms missing the object and in that case, they fail to categorize and report it to the system. Some possible reason could be discontinuous data, very few data points or low-resolution images. This algorithm is specialized in discovering the structure from data points. Clustering describes the class of methods and class of problem like regression.

The clustering algorithms methods are organized typically by modelling the approaches like hierarchical and centroid-based. All methods of this algorithms are concerned with utilizing the inherent structures in data to organize the data perfectly into groups of maximal commonality. The most commonly used algorithm are K-means, Multi-class Neural Network etc.

**E. Neural Network Regression**

Neural network algorithms are utilized for regression, classification or unsupervised learning. They group the data that is not labelled, classify that data or forecast continuous values after supervised training. This neural network algorithm normally use a form of logistic regression in the final layer of the net to change continuous data into variables like 1 or 0.

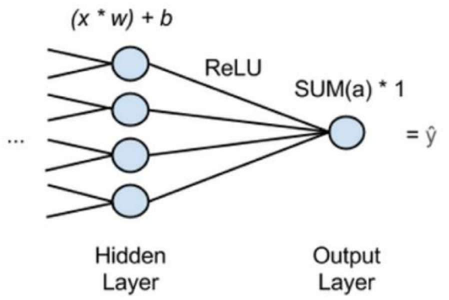


**Figure 1.** Neural Network[10]

From above figure, 'x' is the input, features passed forward from the previous layer of the network. Into every node of last hidden layer, many x's will be fed and every x will be multiplied by w, a corresponding weight and to a bias, the products' sum is added and forwarded to an activation function. ReLU (rectified linear unit) is an activation function used commonly, as it does not saturate on the shallow gradients like the sigmoid activation functions do. ReLU provides an output activation for each hidden node and the activations are added going into output node which passes the sum of activations. This implies that a neural network that performs regression contains single output node and this node will multiply the sum of activations of previous layer by 1. The network's estimate, 'y hat' will be the result. 'Y hat' is the dependent variable that all the x's map to. You can use the neural network in this way to obtain the function relating x (number of independent variables) to y (a dependent variable) that you are trying to predict[11].

**F. Pattern Recognition Algorithms (Classification)**

Advanced Driver Assistance Systems (ADAS) is a sensor through which environmental data is obtained in the form of images. And these images are filtered by removing irrelevant data points and after that only helpful data is remained. Recognition of patterns is an important step in a dataset before classifying the objects and this algorithm known as data reduction algorithm.

Dataset edges and polylines (fitting line segments) of an object as well as circular arcs to edges are removed with the help of data reduction algorithm.

The commonly used recognition algorithms in ADAS are PCA (Principle Component Analysis) and HOG (Histograms of Oriented Gradients), the SVM (Support Vector Machines). The K-nearest neighbour (KNN) and Bayes decision rule are also used.

## IV. RL IN SELF-DRIVING CAR

Reinforcement learning can be seen as a trial and error approach. As the agent is not explicitly told which action to take, it can only evaluate the actions with the rewards it received. For this evaluation to be efficient, the agent has to continually interact with the environment and adapt its strategy with regard to the rewards it gets. The immediate reward depends on both the action taken and the state the agent is in.

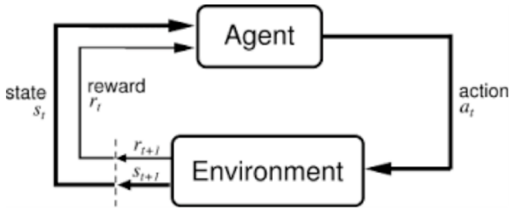


**Figure 2.** Reinforcement learning schema[12]

### A. Markov Decision Process

A finite Markov decision process is a tuple S, A, T, R, γ where • S is a finite set of states, • A is a finite set of actions, • T is the state transition probability function, • R is the reward function, • γ ∈ [0, 1] is the discount factor[13].

### B. Q-Learning

This value iteration algorithm uses explicitly the state transition probability function T and the reward function R of the MDP. However, it is usually assumed that the model, which consists of knowledge of T and R, is unknown. In this case, we distinguish between two approaches. Model-based algorithms attempt to learn the model and use the estimate of the model to compute an optimal policy while model-free methods focus on learning the state value function and use these estimates to get an optimal policy. Such methods are generally known as temporal difference methods.

### C. Exploration-Exploitation Trade-off

As stated earlier, the agent follows some policy that dictates its actions. We should then ask ourselves how the choice of this policy influence the Q-learning algorithm. In Walkins and Dayan , it is proven that the Q-values converge to the optimal Q∗ if two conditions are met. One of them states that every state-action pair has to be visited infinitely often. Consequently, the agent's policy needs to respect this condition. For this, we could simply use a policy where the actions are always chosen randomly with a uniform distribution over the action space. However, the global performance of the agent during the learning phase will be poor; we want it to maximize its return. These two opposite behaviours are called exploration and exploitation.

### D. Function Approximation

A substantial drawback of Q-learning is that storing the Q-values of every state-action pair becomes incredibly difficult or even impossible when the state space is very large or continuous. Moreover, the convergence's condition we tackled earlier, which states that all the state-action pairs must be visited infinitely often by the agent, becomes very difficult to respect as well. In other words, there is never enough training data in these cases. One solution is to use a function approximation that approximates and generalizes the Q-values across the states instead of computing a value for each state-action pair. We thus build a function Qˆ(s, a) which approximates the real Q-value function Q(s, a). This is a parametrized function whose parameters must be learned from experience.

## V. CONCLUSION

We wondered if it was possible to train self-driving cars capable of driving safely and consequently designed different neural network models; we designed three simple networks – without convolutions – and two convolutional networks in order to try to solve this problem with deep reinforcement learning. We first trained our models for a single-agent environment to see if a learning agent was able to learn the human drivers' behavior and develop a good driving strategy. We showed that it was indeed possible and even achieved high performances. However, as the training is done in one fixed setting of the highway, the models' aptitude to adapt to a new setting of the environment – higher traffic density, human drivers' irrationality – is not always good. Afterwards, we tested our single-agent trained models in a multi-agent environment where all the autonomous cars use this trained model. We saw that, for most models, these results were unsatisfactory, which is probably caused by the fact that the autonomous cars' learned behaviour differs from the behaviour of human drivers – but they only learned how to deal with human drivers. Finally, we trained models in a multi-agent setting in three different ways. We first considered the exact same models that we used for the single-agent environment and showed that most of them, even the ones that had a good performance in a single-agent setting, did not learn efficiently. We then modified these models to add information regarding the multi-agent nature of the environment: a distinction between the human drivers and the autonomous cars. We showed that these models performed better than their single-agent version, although we did not achieve the same level of performance as we did for the single-agent environment. Lastly, we used networks that were already trained in a single-agent setting as the starting models for the multi-agent training. The best performances over all the multi-agent training experiments we did were obtained with these "re-trainings" of single-agent models.

## VI. FUTURE SCOPE

First, we only considered one possible setting of the highway, a simple one without exits; consequently, we would like to reproduce the same experiments for a version of the highway with exits, to see how the agents perform when they have different possible goals. The next logical step of this work would be to do more trainings by varying all the possible parameters in order to find optimal values for these parameters. A tool such as irace1 could be used to optimize the training configuration. All our models were trained with a fixed traffic density, thus limiting the number of situations the learning agents can encounter. An interesting improvement would be to use a varying traffic density during the training; furthermore, the traffic density could follow some probability distribution representing something similar to the rush hours in traffic. As far as our traffic simulator is concerned, we can think of multiple possible improvements that would make the whole system more realistic. For example, introducing the notion of good or bad drivers; a driver's aptitude to drive could impact their irrationality or their sight. Another improvement would be the addition of other types of cars in the simulator: namely, trucks, which would block the field of view of the cars in their vicinity. Finally, making a continuous version of the highway could also be interesting.

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