Machine Learning for Autonomous Driving Decision-Making

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1. Introduction to Autonomous Driving

Autonomous driving is a collection of technologies that allow a vehicle to sense and perceive the physical and social environment, model and plan its driving behavior, and then make decisions based on a cost versus benefit analysis. The promise of autonomous driving is to create a safer system, with less congestion and a better user experience, that can operate at scale without significant manual intervention.

The definition of five levels of vehicle autonomy ranges from 0 to 5. Vehicles with level 0 autonomy have no automation and drivers execute all vehicle control tasks. With increased system capability, level 1 vehicles have some driver assist features while level 2 vehicles can autonomously control speed and steering but require driver attention. At levels 3, 4, and 5, vehicles operate with increasing autonomy and decreasing reliance on driver attention and intervention. Machine learning has been a part of the intelligent systems used in autonomous driving for decades. The rise in the use of machine learning is directly associated with the ability to capture, store, and process the vast amount of data generated by these highly automated vehicles.

The interest in and potential market for autonomous vehicles is significant. Worldwide, it is estimated that over 1.3 million people die annually due to road traffic crashes. Although those numbers have dropped in recent years in many places, new safety technologies are anticipated to provide greater reductions. In the United States, it is estimated that in 2016 traffic crashes cost over 90 billion dollars in lost productivity and over 160 billion dollars in lost wages. Injuries cost an estimated 79 billion dollars. The manufacturing sector continues to hold that as their largest worker-related compensation issue. Decades from now, those costs could approach zero with the adoption of safer vehicles and autonomous interventions. These are some of the reasons that manufacturers, federal and state governments, and the research and academic communities continue to work together to make the potential of autonomous vehicle operation a reality.

2. Fundamentals of Machine Learning in Autonomous Systems

This section delves into the principles of machine learning as they pertain to autonomous systems. It discusses various approaches and techniques used to enable vehicles to learn from data. The differences between supervised, unsupervised, and reinforcement learning are clarified. Important concepts such as neural networks and deep learning are introduced, presenting their roles in processing complex data. The relationship between sensor data and machine learning algorithms is emphasized. Real-world applications of machine learning in various aspects of autonomous driving are explored. This background prepares the reader for a deeper understanding of how these fundamentals impact decision-making in driving.

There are several approaches where data is used to enable the learning of a vehicle: supervised learning, unsupervised learning, and reinforcement learning. With supervised learning, there are input-output pairs of data for which the output is already known. Autonomous systems require vehicles to learn from sensor measurements, but it is not possible to measure what correct action the vehicle should have executed while learning. Consequently, unsupervised learning is not applicable in autonomous systems. In addition, reinforcement learning is not practically appealing for many reasons, such as the policy learned may not converge, may not exist, or may be difficult to compute.

Instead, one of the most popular and practical machine learning approaches used to enable vehicles to learn from data is supervised learning. Machine intelligence makes use of many learning concepts. For instance, deep learning is used to train very large neural networks and is applicable whenever an important part of the problem is to find patterns in data, if the system can learn from a large amount of data, and regarding both consequences and predictions when all the relevant information cannot be specified and must be learned. This is particularly powerful for developing autonomous systems because the environment and the resulting input to the system are complex and difficult to predict, and the autonomous system must be able to predict future changes in the environment given past and current observations. Key to this is a machine learning system's capability to model the underlying environment, which in essence is found by remaining adaptive to changes while given data to learn from.

3. Real-Time Path Planning Algorithms

Autonomous driving requires algorithms to safely navigate in dynamic environments. These algorithms need to provide robust and efficient solutions in real-time. Real-time path planning is crucial for planning movements for autonomous vehicles. Different approaches to path planning have been employed based on the requirements of the specific setup in which the autonomous vehicle is operating. The real-time path planning algorithms attempt to take any collision avoidance constraints in dynamic setups into account when choosing an optimal path.

Dijkstra's algorithm and A* search are popular algorithms used to find the shortest path on a graph from the initial state to the final state with a positive path cost. Dijkstra's algorithm explores the nodes in a greedy manner utilizing uniform distribution. A* search utilizes a cost heuristic along with the known cost to reach any visited node towards the initial node from the initial state. Upon discovering a low-cost heuristic node towards the final state, a sequence path can be reconstructed.

Both Dijkstra's algorithm and A* search result in suboptimal trajectories. Dijkstra's algorithm discovers nodes that should not have been reached in the first place simply because of the accumulated cost over fewer iterations. Furthermore, its performance exponentially increases with increasing graph density, which can be the case for a finer grid representation. The main strength of Dijkstra's algorithm lies in any uniform cost graph. For an unknown uniform cost graph, Dijkstra's algorithm can be used to locate the final node from the initial node. Tagged A* search overcomes A* search's weak performance with a replay strategy that applies another relaxed least costly found operator to reconstruct the final path. Reinforcement learning is also employed to solve the shortest path search. Directed Q-learning learns the driving policy regime based on feedback without the knowledge of the real-world dynamics.

Dijkstra's algorithm discovers nodes that should not have been reached in the first place simply because of the accumulated cost over fewer iterations. Dijkstra's algorithm performance exponentially increases upon increasing the percentage of cells over the total area. Dijkstra's algorithm is especially beneficial whenever unknown graph weights have to be imposed across experience. Implementation of graph algorithms in control systems is complex and involves recursive and nested loops to update the cost to any reachable state. Extremely low planner frequency rates for specific applications that require complex data for

real-time operation can be facilitated with a good path-saving technique. Path-saving techniques are available in real-time A* algorithms. With Dijkstra's algorithm, totally unnecessary iterations could result in computing a coated graph that requires time. Dijkstra's algorithm is not seen as data-intensive since it would explore a few states in shallow depth before branching.

3.1. Dijkstra's Algorithm and A* Search

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Dijkstra's algorithm is a pathfinding and graph traversal algorithm that systematically finds the shortest path between nodes in a graph. In the context of autonomous driving, nodes are interpreted as possible positions of the vehicle at a specific instance of time, whereas edges between nodes represent permissible transitions between those positions. Dijkstra's algorithm was employed for path planning within urban driving environments, i.e., those with non-uniform edge costs, and for lateral path planning within highway environments, i.e., those with uniform edge costs. Since time constraints render suboptimal planning algorithms desirable for autonomous onboard decision-making, we have employed Dijkstra's algorithm for the generation of short paths. Dijkstra's algorithm visits nodes in an order determined by their shortest-path estimates. It subsequently revises the shortest-path estimates of nodes that can be reached from each node. In each step, Dijkstra's algorithm adds the node with the smallest shortest-path estimate to a set of visited nodes.

A* search is a notable enhancement to Dijkstra's algorithm that employs an admissible and consistent heuristic function to reduce computational complexity. A* search was employed within the autonomous vehicle's decision-making process for longitudinal path planning within extended highway environments, i.e., those with on- and off-ramp edge connections. Adaptive precision of the heuristic function was used in order to dynamically adjust the balance between optimality and computational expense. The heuristic employed was informed by a grid map, where path costs consisted of the continuous road segment costs and the ramp edge costs. A heuristic function informed by such a map is consistent because it does not overestimate the remaining distance through the road. Both Dijkstra's algorithm and A* search exhibit a computational complexity that is exponential in the number of vertices when using a priority queue. For large numbers of vertices, this drives complexity to O((V + E)

log(V)), where E and V are the number of edges and vertices, respectively. The decision to apply the more computationally complex A* search was guided by comparison of the number of graph vertices to the computational complexity of both algorithms.

Dijkstra's algorithm and A* search are suitable for scenarios in which planning is applied to a dense node graph. A substantial portion of the literature has applied these algorithms to road navigation. The shortest paths in the below figure were generated via Dijkstra's algorithm and depict urban driving trajectories. The paths evidence the vehicle's ability to deviate from its final destination in search of more optimal edges. However, both algorithms divert the vehicle following a specific edge in order to reach a desirable destination location, rather than to minimize travel time. Such diversions suggest that the variants of A* search in this context may be adapted to minimize driving time with an extension to the cost function. Defects in trajectory quality arise via Dijkstra's algorithm during highway navigation; the algorithm's implementation without the evaluation of lateral position renders short yet undesired lane changes. Such defects may be mitigated via an examination of the gap acceptance model. Since A* search further reduces on-road computational demand, both variants likely present realistic optimization possibilities.

3.2. Reinforcement Learning for Path Planning

Reinforcement Learning for Path Planning: Reinforcement learning (RL) has gained tremendous interest and reputation in autonomous systems, including autonomous driving scenarios, in which a skillful or optimal path has to be facilitated. As one of the most promising machine learning paradigms, RL allows an agent to learn to make decisions by interacting with an environment. During the learning process, the agent accumulates experiences, named samples, where each sample involves the environment presented to the agent, the action decided by the agent, the environment feedback as the consequence of the action, the computational reward associated with the agent, and the representation of the agent's perception at that moment. Among these elements, the environment state, the action to determine, and the rewarded return are commonly used to define and formulate an RL problem. In the spatial navigation literature, the state refers to the status or geographical coordinates of the environment presented to the mobile robot. The action normally stands for the change of the vehicle location based on the available environment perception. The reward

is anticipated to motivate the agent's learning for making a profitable decision when acting in navigation tasks to reach a destination on the map.

Random exploration leads not only to a higher chance of learning better policies in navigation tasks but also to the computational complexity of states. For example, if the agent's state space grows exponentially with the complexity of the environment and becomes much larger than the length of the training phase, the ability to find an optimal strategy based only on the training done is compromised. As a consequence, the concept of temporally varying value functions, so-called Q-functions (whose value indicates the utility of specific actions from specific states), combined with sample-based update rules forming the base of powerful value-based reinforcement learning algorithms, one of which is the nifty class of Q-learning meta algorithms, includes neuromodulated Q-learning as a novel member. In particular, Deep Q-Networks algorithms, one of the modern versions of Q-learning, integrate the flexibility of deep learning with sophisticated meta-updates for enhancing learning efficiency. They have attracted the most attention for employing pre-training and then fine-tuning on RL agents conveyed sensor data or spatial map data to make them master the highly task-oriented navigational policies. Side-by-side performance improvements based on constrained sparsity computations together with synaptic weight pruning have been proposed for developing state-of-the-art Deep Q-Networks ensembles. The ability to adapt to newly observed, exploited, and emphasized spatial zones in navigation scenarios with accurate time-varying eligibility traces while minimizing the computational cost of the Q-function ensemble can be improved when Deep Q-Networks are modulated by neuromodulation modules. This has huge potential relevance for path planning in projects since reinforcement learning, especially the latest version, can be trained with simulated data and adjusted to the real world, e.g., online self-driving vehicles updated.

4. Hazard Detection and Object Recognition

Hazard detection and object recognition are crucial for the safety of autonomous vehicles. The traditional approach to detect objects based on image processing found low-level image features and used various clustering algorithms for lane detection, often resulting in combining several models into one system. The transition from using traditional to more contemporary techniques of describing and detecting objects based on a large number of low-

level features and classifying them into various groups, or simply with the help of deep learning methods, has contributed to increased accuracy and reliability in the decision-making process in autonomous vehicles. In the domains of ADAS, hazard detection is based on the extraction of features from the environment, like infrastructure, while obstacle detection is used for complex scenarios where sensors could not directly extract data from the hazard.

The detection of surrounding objects has been studied over the past two decades. An apex of comprehensive techniques for deep learning-based object detection has been proposed to solve detection-related issues. This chapter discusses this evolution with the use of different datasets used for training object detection models. This chapter aims to provide an overview of the fundamentals from the hazard detection point of view; it also discusses the importance of timing in making a decision while driving. Hazard detection systems are usually based on sensors such as lidar and radar and are performed at a more global level, assessing a series of data points from the environment in order to detect a potential situation that could cause a series of threats. Detection efficiency and time are mandatory for the decision-making module for autonomously driving systems, as both represent deadlines in which the automated software should make the decision.

4.1. Image Processing Techniques

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4.1.1. Classical Methods One of the most traditional and early studies regarding object detection in image processing is edge detection. It is used to create and represent the objects' contours in the images. Among its techniques, the most well-known is the Sobel filter. Later on, segmentation, feature extraction, and feature matching were used. These techniques were often applied in a sequence. In feature extraction, Canny proposed the use of the combination of three other techniques to improve its performance. Its main purpose is to extract edges from the original images with lower noise and then build naturally continuous regions or boundaries by using gradients. The Canny algorithm applied Sobel for the first derivative calculations, with a Gaussian filter to add the effect of noise reduction and a double threshold method to find the actual relevant edges that complete the continuous boundaries around them. However, this kind of technique has several constraints. Instead of the fuzzy-based

technique, it needs a perfect detection to make any decision afterward. The limitations of previous methods led researchers to shift their focus to modern deep learning. It is important to mention that the versatility is quite limited, and they do not have the ability to adapt themselves to certain dynamic changes. Due to a fixed template that is loaded initially, the system recognizes and follows the pre-loaded object, regardless of whether it is necessary. In a complex driving setting such as a road environment or urban city, every capture could have different appearances because of light, environmental conditions, dirty camera lenses, or more. Normal use for detecting obstacles is also not always used to detect traffic signs, road marks, estimators/distances, and so on. Thus, traditional methods have insignificant effectiveness for dynamic reconnaissance in complex driving situations.

Overall, classical methods work well in structured situations and have broken down in newer, more complex variants. Compulsory image pre-processing, to emphasize some features in particular, was important in their method. In this scenario, the need for image analysis with machine learning is important because it does not require image preprocessing specifically. The development of deep learning in computing technology and data handling helped it to be applied to various fields, including autonomous driving, and it was able to compete with traditional methods.

4.2. Deep Learning for Object Detection

Deep learning methods have had a significant impact on advancing the performance of object detection. In the context of autonomous driving, deep learning models have inspired breakthroughs for visual sensory data, allowing a wide range of visual recognition tasks to be improved using image data. Convolutional neural networks (CNNs) have been widely adopted in advancing state-of-the-art results due to the development of more sophisticated and relatively deeper architectures and learning processes. Deep CNNs can provide a considerably higher level of representation for detecting objects from video or image frames. The typical process for training a deep learning model uses a supervised learning procedure with labels. In object detection, side information in terms of object classes and bounding boxes of the training image is provided. Training to minimize errors produced by the model is carried out over an epoch after the whole training dataset has been propagated through the model once. Deep learning architectures for object detection use the training processes to

optimize various layers to understand various scale and translation invariances. Typically, such models require much more computational resources for training due to the high dimensional range of weights and biases needing to be optimized in the forward and backward passes.

Many modern deep learning models have enhanced pioneering efforts, increasing robustness and accuracy for large-scale object detection in RGB images and videos. The You Only Look Once algorithm family produced a strong method for real-time object detection with high generalization for varying classes and scales of objects. State-of-the-art YOLO versions demonstrate detection of objects on par with faster R-CNN methods while being computationally more efficient. Faster R-CNN outperforms traditional methods for object detection, using region proposal propagation methods in a deep learning network. Faster R-CNN uses both region proposal networks for recurrent object detection and a Fast R-CNN for the full scene. The RPN constraint of anchor boxes is not used in single-shot detection as proposed in YOLO. Both YOLO and Faster R-CNN are more effective with the integration of neural networks, providing robustness for object detection across different datasets. The models are able to detect a wide range of objects in various indoor and outdoor environments and can generalize across diverse datasets. Object detection mechanisms have the ability to identify hazards from the surrounding environment and provide critical feedback to the control loop in order to make the car safely drive autonomously. Deep learning object detection and visual recognition models are a vital component of many autonomous driving systems. The deep learning models form part of the sensing component of an autonomous platform. Moreover, object detection is often used within the data-fusion sensing component, combining different precision modalities and sensory data along with the visual scene images.

5. Collision Avoidance Strategies

Collision avoidance is the most crucial part of an AV system, as accident avoidance minimizes the chance of beliefs accumulated during highway driving. At an average of 183 meters per second, nonetheless, choices have to be made rapidly. In general, collision avoidance can be handled as prediction and prevention. Often, vehicles infer the behavior of other road users, which seems singularly true for human drivers who stay focused on sensorimotor activities. Preventing future collisions is done through reactive and proactive methods that have

different operational frameworks. Finally, perception is configured to detect probable obstacles, people, and other objects and events. Sensor data is weakly described by the subject; accidents are not categorized as probable events but are treated as improbable, mostly due to a lack of information.

Sensor data, as well as driving history, are utilized by traffic forecasting to generate a variety of potential paths. In a similar fashion, other inter-vehicle interaction types are anticipated for next-generation vehicles. Information is not only gathered from a range of origins and filtered to acquire reliable messages, but it is often combined from several sources to attain situational awareness. For decision-making purposes, sensor information is translated into required steps. There are many techniques to resolve this challenge of fusing data from multiple sensors. When it comes to the accident avoidance system, the choice created by the complementary algorithm has priority only if operational planning would seem to be dangerous. Achievable travel pathways are generated by the potential threat levels delivered in the execution system. In a variety of investigations, the significance of sensor fusion strategies was seen when the objective was estimating any parameter.

5.1. Sensor Fusion Techniques

One of the significant elements that lead to the advancement of perception in autonomous vehicles is sensor fusion techniques. Deliberately integrating the information extracted from a set of various sensors, such as cameras, LiDAR, radar, etc., ensures the minimization of their respective weaknesses, thus combining their strengths. Cameras are definitely one of the most popular sensors for fundamental image processing and segmentation purposes. LiDAR is accurate in delivering profound information regarding structure and depth sensing in the surroundings of the vehicle. Nevertheless, cameras can be severely affected by low-visibility conditions, for instance, heavy rain, fog, or extreme lighting settings. LiDAR also depends on light reflection, so it may find it difficult to detect thin or transparent obstacles. Fortunately, in such cases, radar proficiently senses both solid and liquid objects. The most complementary sensors are the combinations of LiDAR with cameras and LiDAR with radars. This approach is anticipated to deliver more organized and precise information in extracting vehicle surroundings and participant detection.

The potential strengths and weaknesses of sensors considered in autonomous vehicles reveal why the need for different types of sensors is inevitable and why their accurate fusion in the perception and environment module is crucial. A few of the highlighted challenges in multi-sensor data fusion for perception in autonomous vehicles entail the difficulty of synchronizing different sensors, the inconsistency of data recordings from different sensor systems, formats, and resolutions, and the inability to fuse the enormous amount of input data in real-time. Data inconsistency may comprise different resolutions, distances, and percentages of coverage, e.g., when LiDAR mainly covers the road environment and radar covers the objects behind the vehicle. In this context, choosing a combination of several sensors is worthwhile to avoid data inconsistency and diversified demands among applications of autonomous vehicles for real-time decision-making. Algorithms commonly employed in the fusion module include Kalman filtering, Bayesian networks, and Monte Carlo methods. The efficient fusion of the information from different sensors used in perception is a vital task, thereby dictating the output of the decision-making process and collision avoidance mode. Recent developments in machine learning strategies are entailed, showing enhancements in LiDAR, radar, and camera information.

5.2. Decision-Making Algorithms

Designing a decision-making algorithm is very important because it enables the vehicle to properly drive and interact safely with its surrounding traffic and environment. Several decision-making algorithms have been proposed, each designed to interpret sensor information, make decisions according to traffic rules, generate safe trajectories, and optimize driving motives regarding some objective functions. Usually, one of the primary concerns for driving decision-making algorithms is safety; however, other components such as comfort and efficiency of the driving decisions must also be considered and balanced through the decision-making process. Additionally, the driving decision-making algorithms should also be able to blend information from different sources and handle uncertainties in the environment. In highways, the decision-making algorithm must be able to plan long-term routes and adapt them according to the traffic conditions, whereas in urban scenarios, short-term decisions are typically enough to properly navigate the streets.

The scope of the decision-making algorithms should be adaptable or flexible enough to optimally make decisions according to each situation scenario. Integration with other parts of the AD system is important to validate the driving decision-making subsystem and evaluate their performance. Machine learning algorithms have become more popular in the decision-making system of self-driving cars in order to endow the decision-making algorithm with more flexibility and adaptability that can handle complex urban environments. Decision-making models using machine learning techniques are agile in handling complex multi-agent movements and complicated dynamic environments. However, machine learning algorithms inherently suffer from the problem of how to generalize easily to unknown conditions or how to handle non-generalized situations, which are inadequacies for real-world applications involving driving tasks. The machine learning-based models cannot guarantee the performance of deep neural networks and uncertainties in properties.

6. Challenges and Future Directions in Autonomous Driving

The development of autonomous vehicles is a complex task, the success of which depends on several issues. Apart from the technical difficulties associated with processing a vast amount of data in real time, largely affected by the environmental non-deterministic variability, one of the greatest problems is related to safety issues. The reliability of the autonomous vehicle system is not only related to the car's behavior itself but also to the decisions that the car makes under given critical conditions. In this regard, ethical considerations become essential in the development of the decision-making algorithm that works in case of a critical event: identifying the methodology adopted by the entity that has to devise the car's behavior in a given situation becomes a mandatory task. Collaboration between the industries is the way to implement guidelines for these kinds of decision-making algorithms. The development of autonomous driving can be seen as a binding task between technical and legal dimensions, where the vehicular industries have to interact with the legal sphere to deal with the necessity of guidelines and fences delimitation for the technical issue resolution. It is necessary for driving and fleet decision-making algorithms to comply with behavioral models intended for human drivers in relation to vehicular or pedestrian behavior. An in-depth analysis of this interdisciplinary cooperation is the objective of the Spillover section, which is currently in an acceptance phase.

Despite the considerable technological advances that occurred in the last years, there are myriad challenges that have to be tackled before mass deployment of autonomous vehicles can be achieved. Research on developing new approaches that can potentially tackle all these challenges must be fostered, trying to investigate the limit situations of the technologies available today. AI can and must be heavily involved in this effort. This effort to improve the new technologies available through artificial intelligence systems must be based on the testing of various databases, considering possible irregularities in these. Simulation can help in many aspects, but only a real-life database can be used to evaluate the active learning and generalization of an algorithm or the effective communication of autonomous vehicles with other controllers, as well as other systems available today. The development of increasingly advanced communication algorithms must be another direction for research and development. In addition to current and active radar sensors, LIDAR, and cameras installed in vehicles, the communication of these vehicles with infrastructure sensors or sub-networks or a cooperative sensor-based environment is a great advantage.

7. Conclusion

The aim of this chapter was to comprehensively survey autonomous driving decision-making and the recent advancements. In particular, we are excited about machine learning-based techniques because of their capability to unlock solutions to problems where traditional methods have failed. We surveyed many state-of-the-art decision-making techniques focusing on different aspects, the most important of which are real-time path planning, hazard detection, and decision-making algorithms. It seems that autonomous driving has a really bright future. However, there are still many challenges to overcome. On the technical level, sensor technologies and machine learning are still not perfect, and therefore many crashes still occur. In addition, there are always going to be ethical questions concerning the decision-making of autonomous vehicles; these decisions should be aligned with the safest possible approach. Clearly, a lot of research and progress still needs to be made. More research is needed in all these aspects. As of now, the field is very young and generally fragmented, and there are no standards and benchmarks. It goes without saying that autonomous vehicles will certainly be safer if their surroundings are also inhabited by autonomous vehicles. For that to happen, the convoy of companies must work together harmoniously; otherwise, it's impossible.

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