Towards Safe, Explainable, and Regulated Autonomous Driving

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ABSTRACT
There has been recent and growing interest in the development and deployment of autonomous vehicles, encouraged by the empirical successes of powerful artificial intelligence techniques (AI), especially in the applications of deep learning and reinforcement learning. However, as demonstrated by recent traffic accidents, autonomous driving technology is not fully reliable for safe deployment. As AI is the main technology behind the intelligent navigation systems of self-driving vehicles, both the stakeholders and transportation regulators require their AI-driven software architecture to be safe, explainable, and regulatory compliant. In this paper, we propose a design framework that integrates autonomous control, explainable AI (XAI), and regulatory compliance to address this issue, and then provide an initial validation of the framework with a critical analysis in a case study. Moreover, we describe relevant XAI approaches that can help achieve the goals of the framework.

KEYWORDS
intelligent transportation systems, autonomous driving, explainable artificial intelligence, regulatory compliance

1. Introduction

Autonomous driving is a rapidly growing field that has attracted increasing attention over the last decade. According to a recent report by Intel, the deployment of autonomous cars will reduce on-road travel by approximately 250 million hours and save about 585,000 lives per year between the years 2035 and 2045, just in the USA \cite{Lanctot2017}. While these advantages certainly encourage the use of autonomous vehicles, there is also major public concern about the safety of this technology. This concern arises mainly from reports of recent accidents \cite{Stanton2019, Yurtsever2020, NTSB2020} with the involvement of autonomous or semi-autonomous cars, primarily attributed to improper use of semi-autonomous functions. This issue is a major drawback, impeding self-operating vehicles from being acceptable by road users and society at a wider level. As artificial intelligence techniques power autonomous vehicles’ real-time decisions and actions, a malfunction of the vehicle’s intelligent control system is considered the main focus of analysis in such mishaps. Hence, both road users and regulators require that the AI systems of autonomous vehicles should be “explainable,” meaning that real-time decisions of such cars, particularly in critical traffic scenarios, should be intelligible in addition to being robust and safe. In this case explainability needs not only to provide transparency on an individual failure but also broadly inform the process of public transportation regulatory compliance \cite{Slagter2021}.

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Safe Regulatory compliant Explainable

Real time perception mapped to a relevant action under traffic rules

Stopping because red traffic light is on and there are pedestrians crossing the road.

Figure 1. A graphical illustration of an autonomous car on its perception-action mapping that is safe, explainable, and regulatory compliant. *Safe* because the vehicle drives under traffic rules and does not hit people and touch other objects. *Explainable* because the vehicle provides a rationale for the taken action. *Regulatory compliant* because the vehicle follows all the traffic rules and guidelines. The red-colored text implies perception and the green-colored text is the corresponding action. An image in the left corner from [Litman 2021].

Voster 2017; Dentons 2021. Urging the right to an explanation, several regulators have established safety and compliance standards for intelligent transportation systems. In this context, we are developing a general framework that can make autonomous vehicle manufacturers and involved users improve safety and regulatory compliance, and help autonomous vehicles become more publicly trustable and acceptable. With such a focus, our paper makes the following contributions:

- We propose a general design framework for explainable autonomous driving systems and validate the framework with a use case;
- We present AI approaches from an algorithmic point of view that can help achieve explainability in autonomous driving and provide rationales behind an automated vehicle’s real-time decisions.

The rest of the article is structured as follows. In Section 2, we provide a brief overview of modern autonomous driving and show the need for explainability in this technology. We introduce a relevant design framework in Section 3 and substantiate it with a case study in Section 4. Finally, in Section 5 we provide potential AI approaches that can help attain explainable autonomous driving systems and sum up the article with conclusions.

2. A glance at state-of-the-art autonomous driving

Autonomous cars, also known as self-driving or driverless cars, are capable of perceiving their environment and making real-time driving decisions with the help of intelligent driving control systems. To capture the operational environment, autonomous vehicles leverage a variety of passive sensors (e.g., collecting information from the surrounding without emitting a wave, such as visible spectrum cameras) and active sensors (e.g., sending a wave and receiving a reflected signal from objects, such as lidar). Sensor devices detect changes in the environment and enable the driving system of the car to make real-time decisions on the captured information ([Campbell et al. 2018](#) [Yeong et al. 2021](#)). Current autonomous vehicles deployed on real roads are classified as having different levels of automation. SAE International has defined six different levels of autonomous driving based on the expected in-vehicle technologies...
and level of intelligent system, namely Level 0 - No automation, Level 1 - Driving assistance, Level 2 - Partial automation, Level 3 - Conditional automation, Level 4 - High automation, and Level 5 - Full automation (Shuttleworth 2019). The anticipated increase of automation levels escalates reliance on an intelligent driving system rather than a human driver, particularly in Level 3 and above. However, such vehicles, even at Level 3, have recently caused several road accidents, cited above, that have led to severe injuries or even loss of human lives. Why did the accident happen? What malfunction of the driving system led to the crash? These questions naturally raise serious ethical and safety issues and provide the motivation for explainable AI (XAI) systems. In this context, the General Data Protection Regulation (GDPR) of the European Union (EU) established guidelines to promote a “right to explanation” for users, enacted in 2016 and carried into effect in May 2018 (GDPR 2016).

In another example, The National Highway Traffic Safety Administration (NHTSA) of the US Department of Transportation has issued a federal guideline on automated vehicle policy to attain enhanced road safety (NHTSA 2016). Current and future generation autonomous vehicles must comply with these emerging regulations, and their intelligent driving system should be explainable, transparent, and acceptably safe. In this regard, we propose a straightforward framework that considers the motivation for these requirements and then identify computational and legislative components that we believe are necessary for safe and transparent autonomous driving.

3. An XAI framework for autonomous driving

We present a general design framework in which methods for developing end-to-end autonomous driving, XAI, and regulatory compliance are connected. In this approach, the framework consists of three main components: (1) an end-to-end autonomous systems component, (2) a safety-regulatory compliance component, and (3) an XAI component. Explainability in the context of autonomous driving can be thought of as the ability of an intelligent driving system to provide transparency with comprehensible explanations 1) for any action, 2) to support failure investigation, and 3) in support of the process of public transportation regulatory compliance. We describe the role of the aforementioned components individually in the following subsections.

3.1. An end-to-end autonomous systems component

We need a simple but precise description of what we mean by “end-to-end autonomous systems.” To start, we need to be able to refer to the set of actions that any autonomous vehicle is capable of executing. We consider the set of possible autonomous actions of automated vehicles as

\[ A = \{a_1, a_2, ... a_n\}. \]

Notice we consider the list of executable actions as a finite repertoire of actions that can be selected by a predictive model, whether that model is constructed by hand or by a machine learning algorithm or by some combination. Example actions are things like “turn right,” or “accelerate.” For now, we refrain from considering complex actions like “decelerate and turn right” but acknowledge such actions will be possible in any given set \( A \) of actions, depending on the vehicle.
We use the notation $C$ to denote an autonomous system controller and $E$ to denote the set of all possible autonomous system operating environments. The overall function of an end-to-end controller is to map an environment $E$ to an action $A$; we have an informal description of the role of the autonomous system controller as

$$C : E \mapsto A.$$  

This mapping is intended to denote how every controller’s responsibility is to map a perceived or sensed environment to an autonomous system function. We can provide a descriptive definition of an end-to-end autonomous controller as follows: A control system $C$ is an end-to-end control system or $eeC$, if $C$ is a total function that maps every instance of an environment

$$e \in E$$

to a relevant action

$$a \in A.$$  

Even with such a high-level description, we can note that the most essential attribute of an $eeC$ is that it provides a complete mapping from any sensed environment to an action selection. We want this simple definition because we are not directly interested in sub-controllers for sub-actions; we are rather interested in autonomous controllers that provide complete control for high-level actions of any particular autonomous system, and which can be scrutinized for safety compliance for the whole scope of autonomous operation. Therefore, the $eeC$ component is primarily responsible for perceiving the operational scene accurately using sensors such as video cameras, ultrasonics, lidar, radar, and other sensors, and enabling the car to take relevant actions.

### 3.2. A safety-regulatory compliance component

The role of our framework’s safety-regulatory component, $srC$, is to represent the function of a regulatory agency, whose primary role is to verify the safety of any configuration of $eeC$ for an autonomous vehicle’s repertoire of actions $A$.

We first note that safety compliance is a function that confirms the safety and reliability of an $eeC$ system. This could be as pragmatic as an inspection of individual vehicle safety (e.g., some jurisdictions require processes that certify essential safety functions of individual vehicles for re-licensing), but more and more is associated with sophisticated compliance testing of $eeC$ systems from manufacturers, to establish their public safety approval (e.g., Transport Canada (2021)). The $srC$ components will vary widely from jurisdiction to jurisdiction (e.g., Dentons (2021)). In addition, AI and machine learning techniques have largely emphasized the construction of predictive models for $eeC$ systems. We can also note that all existing methods for software testing apply to this $srC$ task, and we expect the evolution of $srC$ processes will increasingly rely on the automation of compliance testing against all $eeC$ systems. The complexity of $srC$ systems lies within the scope of certified testing methods to confirm a threshold of safety. For example, from a compliance repertoire of $N$ safety tests, a regulator may require a 90% performance of any particular $eeC$. With these expectations, the $srC$ component should guarantee the following safety concepts as defined by Reschka (2016)’s work:
• An autonomous car does not hit any static or dynamic objects on the road
• An autonomous car understands its performance abilities on the road
• An autonomous car does not block the traffic whether it is in motion or in a parking state
• An autonomous car does not exceed the speed limit specified in a road segment
• An autonomous car does not block the routes of an emergency vehicle
• An autonomous car watches out for cars driving at a red traffic light
• An autonomous car gets ready for a takeover by a backup driver in case automation capabilities are lost or malfunction

Thus, a proper combination of the $eeC$ and $srC$ components is a key to the correctness of the autonomous driving software system.

3.3. An XAI component

The third component of our framework is a general XAI mechanism. At the highest level, the XAI component of our framework is responsible for providing transparency on how an $eeC$ makes a selection from a repertoire of possible actions $A$. While the $eeC$ and $srC$ components have always been part of traditional autonomous driving systems, the explainability ability in real-time decisions remains unclear in the current state of the art. In particular, providing explanations in critical driving decisions is an essential factor to establish trust in the automation capability of autonomous driving technology. The difficulty of the challenge is directly related to those methods used to construct the control mechanism $C$ of the $eeC$. For example, a machine learning technique will need to address the selection of actions based on the interpretation of the sensed environment as accurately as possible. This challenge is coupled with the demands created for the “explainee,” which may range from natural language interaction with a human driver (e.g., why did the system suggest having the driver take over steering?) to the potentially very complex setting of compliance safety parameters for regulatory compliance testing software. In terms of delivery, the explanations of the XAI component could be communicated in two ways as specified in Figure 2:

- **Textual explanations:** Natural language-based explanations can justify decisions of an automated vehicle linguistically to the stakeholders. For example, if a vehicle changes its route at some time step unexpectedly, it could produce such
an explanation: “Changing predefined route because there is a traffic gridlock ahead.”

- **Visual explanations:** In this case, explanations are delivered to end-users in a visual format. For instance, a passenger can see the visual perception of a car in an interface provided and judge appropriateness of real-time actions with respect to the visual information. Recently, Greydanus et al.’s work, using saliency maps, shows how agents make their real-time decisions in Atari games. So, it would be worthwhile to apply the concept of saliency maps in the form of visual explanations to understand why a vehicle makes particular decisions in specific time steps.

The graphical description of the proposed framework is shown in Figure 2. As indicated, the three components of the framework are interrelated, and each component has a concrete role in the framework.

4. Case study: The role of the framework in a post-accident investigation

Transportation regulators within their specific jurisdictions initiate a set of protocols to analyze the cause of traffic accidents with the involvement of autonomous vehicles. In such cases, the primarily investigated questions are: Who caused the accident? Is this a fault of a vehicle’s autonomous system, or did other road conditions and participants trigger the mishap? It is expected that autonomous cars can perform safe actions in all potential traffic scenarios that human drivers have commonly handled. ISO 26262 has established international safety standards for road automobiles that define safety rules and principles for passenger vehicles (ISO 26262 2011). This standard requires that a self-driving car provide intelligible and evidence-based rationales for the safety of its decisions in the operational environment. Moreover, a vehicle should also provide information on potential residual risks of taking particular actions. As an example, we show a traffic scenario with an accident and describe the role of our framework to help identify the factors leading to this accident and to help further handle the situation appropriately according to traffic regulations.

For our simple case study, we first assume a simple traffic scenario in an uncontrolled four-way intersection where an accident with the presence of an autonomous car (i.e., ego car) and another vehicle happens while both are attempting to make left turns in a given time step $t_n$ (Figure 3). Accident investigators analyze the decisive actions of both cars at that particular time step. Suppose an autonomous vehicle records its action at $t_n$ and provides an explanation as a justification for a taken action and the quantitative description of a residual risk associated with the performed action. Such functionality can help the investigators understand the main cause of the accident, i.e., whether an autonomous or other car took the wrong action. It immediately turns out that providing human interpretable justifications on a history of performed actions is a powerful tool both from a regulatory perspective in a post-accident analysis and from the lens of debugging and improving the existing automated system.

The other benefit of our framework is that it can help diminish the responsibility, liability, and semantic gaps in autonomous driving, as identified by Burton et al. (2020). In terms of the responsibility gap, the framework, with its ability to explain a history of temporal actions, can help regulators and inspectors conclude whom to blame for the mishap. Once the leading actor of the accident is identified, financial responsibility can also be determined, and the liability gap can be resolved. Finally,
A human-operated car
An autonomous car
crash point

Figure 3. A traffic accident in an uncontrolled four-way intersection with autonomous and human-operated cars. Both vehicles try to turn left and incorrect coordination of time and maneuvers leads to a crash. As there may not be witnesses or other helpful arguments, an explainable AI-based driving system, storing a history of explanations alongside the relevant actions of an autonomous car can help understand which party made the wrong decision that caused the mishap. Graphics adapted from Cameron McKay (2021).

the debuggability of intelligent driving can reduce the semantic gap: By inspecting the history of previously taken actions, AI engineers can take the opportunity to improve an existing system by deploying improved AI techniques. Therefore, we see that an intelligent driving system with explainability features and safety verification within the predefined standards has manifold benefits both from legal and consumer perspectives.

5. XAI hereafter: What to expect?

We infer that end-to-end learning and motion trajectory of autonomous vehicles is based on precisely mapping perceived observations to corresponding actions. To date, perception has been mainly carried out through convolutional neural network (CNN) architectures and their augmented variations, and reinforcement learning (RL)-based approaches have proven computationally robust and adequate to map such real-time perception of states to relevant actions. Based on this intuition, we can note that explainable autonomous driving can be achieved by explaining the decisions of some combination of CNN/RL learning architecture. To conform to the framework presented, we provide directions for 1) explainable vision, 2) explainable RL, 3) representation of knowledge acquired from the operational environment, and 4) a question-driven software hierarchy for comprehensible action selection.

5.1. Use of trusted explainable vision: Understanding limitations and improving CNNs

In recent studies, autonomous driving researchers and practitioners have already attempted to leverage CNN-based end-to-end learning. For example, Bojarski et al. (Bojarski et al. 2016b) used convolutional neural networks to map camera inputs to steering actions and obtained impressive results with minimal training data. Their CNN architecture learned a complete set of driving operations for driving in situations with and without lane markings in sunny, rainy, and cloudy weather conditions. In a further work, Xu et al. (2017) combined a dilated CNN with a long-short term memory (LSTM) network to predict a self-driving vehicle’s future motions. Another empirically successful end-to-end learning example from vision is Toromanoff et al. (2020)’s study, where the authors used reinforcement learning along with a convolu-
The car is driving forward because there are no other cars in its lane.

The intelligent driving system produces a textual explanation in a natural language, and a visual explanation with an attention mechanism on a taken action. Original source: Kim et al. 2018.

In addition to the textual explanation, the system also provides visual explanations that highlight the parts of the image that are most relevant to the decision made. This helps to ensure transparency and accountability in autonomous driving systems. The authors of the study conducted an ablation study to prove the effectiveness of their approach by winning the "Camera Only" track of the CARLA competition challenge (CARLA's blog 2019). So, the end-to-end learning approach has demonstrated its effectiveness with an appropriate choice of real-time computational decision-making methods. Consequently, explainable vision-directed actions for autonomous vehicles are based on how high-level features are used to detect and identify objects. CNNs, as the standard deep learning architectures, are "black-box" models, so there is a need to develop explainable CNN (XCNN) architectures to comply with the requirements of the proposed framework. In this direction, there has been recent research on explaining predictions of CNNs: DeepLift (Shrikumar et al. 2017), Class Activation Maps (CAM) (Zhou et al. 2016) and its extended versions such as Grad-CAM (Selvaraju et al. 2017), Grad-CAM++ (Chattopadhay et al. 2018), Guided Grad-CAM (Tang et al. 2019), as well as heuristics-based Deep Visual Explanations (Babiker and Goebel 2017b,a). Motivated by such vision-based explainability methods, some recent studies have attempted to generate visual explanations for autonomous driving tasks. In a related project, Bojarski et al. 2016a developed a method, called VisualBackProp, that shows which set of pixels are primarily and the most influential in triggering the predictions of convolutional networks. Kim and Canny 2017 introduced a vision-based framework using causal attention that shows what parts of an image control the steering wheel for appropriate actions. The authors extended their work in their further study and produce intelligible textual explanations on the vehicle’s actions (Kim et al. 2018). Such post-hoc explanations are a promising step towards transparent autonomous driving and can be helpful to understand critical decisions of an automated vehicle from legislative and stakeholders’ perspectives, as mentioned in our case study.

Taking a further strategic step, in addition to these post-hoc explanations, it is strongly argued that autonomous driving control systems also need to provide intrinsic explanations, where the developed system already becomes interpretable by design (Rudin 2019). While post-hoc explanations are useful for root cause identification in accident analysis, intrinsic explanations can be helpful to prevent such accidents. For instance, a back-up driver or an in-vehicle passenger can see textual explanations of critical decisions of a car with a suitable XAI interface while driving: in case these explanations do not reflect the actual decisions, the back-up driver can control the car with their input (if available) or end the trip and prevent potential accidents in more complicated situations.
There are also at least two additional limitations of CNNs. Firstly, they need an enormous volume of training data to perform well in image recognition and object classification tasks. Moreover, conventional CNNs require all possible orientations of a sample image during training, in order to accurately identify and recognize unseen images which have various orientations and poses. They do not learn pose-invariant objects and this property hampers CNN’s modeling abilities. To overcome this downside of CNNs, Hinton et al. (2011) proposed the concept of capsules, a set of artificial neurons that capture orientation and represent pose parameters such as size, position, and skewing of an object. In their subsequent work, Sabour et al. (2017) they used a dynamic routing algorithm to train information passage between capsules at two successive layers. This feature enables the neural network to detect segments of an image and represent spatial representations differences between them although it is not yet clear how effective this can be. The hope is that the capsule neural network can detect an object in different shapes and poses even if a new sample of the same image has not previously been used in the training phase. Sabour et al.’s most recent work (Sabour et al. 2021) further improves the concept of dynamic routing and learns primary capsule encoders, which detect very tiny pieces of an image.

From the perspective of explainability, the learning mechanism of a capsule network makes this architecture intrinsically interpretable. For example, in the medical domain, Sharoudnejad et al. have empirically shown that likelihood and instantiation parameter vector values provide rational explanations in classification tasks on the 28x28 MNIST dataset and MRI images of patients with brain cancer (Sharoudnejad et al. 2018). Similarly, LaLonde et al. (2020) have shown that their explainable capsule network, called X-Caps, carries human-interpretable features in the vectors of its capsules encoded as high-level visual attributes.

Overall, both explainability and the ability to recognize objects in different poses make CapsNets promising in vision tasks of autonomous driving. In particular, static situations, foreseeable ahead.
road objects such as speed signs and traffic lights often undergo the impact of adverse weather conditions (e.g., snow, wind) and collisions by vehicles that change their stance angle and form (e.g., see Figure 5). As CNNs ultimately require regular shape and orientations of objects for real-time perception, CapsNet can improve their accuracy and consider the likelihood of the aforementioned pose, shape, and position changes along the traffic. Therefore, a CapsNet architecture’s superior abilities with explainability and improved accuracy on object recognition tasks are promising research directions for the vision problems of autonomous driving.

5.2. **Explanation opportunity using model-based reinforcement learning**

Autonomous vehicles make sequential decisions throughout their motion trajectory within a setting formally characterized as a Markov Decision Process (MDP). The field of reinforcement learning (e.g., [Sutton and Barto 2018]) provides an MDP implementation architecture whose high-level goal is to estimate the differential reward of any possible action and to incrementally adjust the priority of making decisions by computing a policy that produces ranking preferred actions. An RL agent’s interaction with the environment as an MDP can be implemented either as model-free or model-based RL. In a model-free setting (such as Q-learning), the algorithm does not have access to the dynamics of the environment (i.e., transition or reward function). It estimates the value function directly from a sensed experience ([Sutton and Barto 2018]). So, model-free RL lacks explainability for learned policies. On the other hand, in the case of a model-based RL approach, an agent firstly tries to understand the world as prior knowledge, then develops a model to represent this world ([Yao and Szepesvári 2012; Yao et al. 2014; Sutton and Barto 2018; Moerland et al. 2020; Kiran et al. 2021]). This approach in model-based RL is known as planning. The idea of planning in RL is essential for understanding the explicit components of decision-making and has powered further model-based architectures (i.e., the Dyna architectures ([Sutton 1991; Sutton et al. 2008; Yao et al. 2009])). While in a model-free setting, an RL agent directly learns a policy with the environment through interaction that produces a reward, in the Dyna and linear-Dyna style architectures an agent simultaneously learns a world model whilst learning an optimal policy through interactions with the world. Such a structure of planning makes it naturally explainable. Whether based on approximations of state descriptions from the world or an imaginary state defined by the model, the planning process uses a model representation to generate a predicted future trajectory. According to the model projection, an “optimal” action is decided at each planning step, which provides a predicted state and a predicted reward. The predicted states and rewards can be analyzed and visualized for the planned trajectory, thus providing an explanation of why the agent favors the choice of a particular action at a specific time step. Within that context, the potential benefits and perspectives of using Dyna architectures and model-based RL are huge for XAI and autonomous driving.

5.3. **Leveraging predictive knowledge**

It is important to specify how an agent could both represent and use the knowledge collected through interaction with the environment. This knowledge can be considered a compendium of predictions that the agent makes in anticipation of a selection from possible actions. Within the RL literature, such an approach to knowledge representa-
tion is called predictive knowledge, and has received significant attention in RL studies (Drescher 1991; Sutton and Tanner 2005; Sutton et al. 2011; White 2015). An agent regularly expects a response from the environment by making many predictions about the dynamics of the environment in accordance with the autonomous system’s behavior. Therefore, predictive knowledge, as one of the essential notions of reinforcement learning, can be considered as prior knowledge about the possible worlds in which the corresponding actions might be taken. In order to consider a prediction as knowledge, a prediction should comply with the requirements of knowledge: first, a prediction should carry fundamental elements of epistemology - justification and truth, in itself (Kearney and Pilarski 2019). Some, for example, (White 2015) and (Sherstan 2020) have shown that General Value Functions (GVFs)(Sutton et al. 2011), an architecture to learn numerous value functions from experience, are a promising proposal for the robust representation of predictive knowledge. In particular, (Sherstan 2020) has empirically validated that GVFs, as a scalable representation, form a predictive model of an agent’s interaction with its environment and can represent an operational environment. Recent works on GVFs have proven their value in perception (Graves et al. 2019) and policy learning problems of real-world autonomous driving (Graves et al. 2020). Motivated by these results, it is beneficial to further investigate the concept of predictive knowledge and its representation with GVFs, to evaluate the robustness of such a formalism for autonomous driving. However, it is noteworthy to point out that GVFs commit to a particular encoding of predictive knowledge, which leaves their explanatory value undetermined.

5.4. Temporal questions and question hierarchies

If there is one common design principle that is shared by the autonomous driving industry, it is the commitment to arrange the control software in a hierarchical structure. To have a self-explainable decision procedure for autonomous driving, it is important that this hierarchy becomes question driven. In particular, the questions frequently arising while driving are those like “Am I going to see the traffic lights turning yellow shortly?”, “Why is the car in front braking?”, “Will the car in the front right of me cut to my lane?”, etc. All these questions seem to come to us naturally when we drive. However, this concept of asking questions receives very little attention from current research on AI methods for autonomous driving. Understanding why human beings have this ability is vital to advancing the safety of autonomous machines. These questions don’t emerge randomly but subconsciously; considering answers to these questions prepares us for a safe drive.

To better understand the usefulness of the question-answering concept, assuming an autonomous car’s intelligent driving system produces such a question-answer pair in a natural language in a particular time step: Q: “Why did the car change its lane?” - A: “Because an obstruction was observed ahead in the current lane.” Such a question-answering pair would mainly be helpful in case of accident investigation, and also could help inspectors to ask further follow-up questions.

From the RL perspective, one potential approach to generate temporal questions based on the ongoing actions would be to use the concept of options (Sutton et al. 1999). Options are the generalized concept of actions that has a policy for taking action with terminal conditions. The option-critic architecture was recently proposed by (Bacon et al. 2017). Both internal policies and terminal conditions of options have been experimentally successful in end-to-end learning of options in the Arcade Learning
Environment (ALE).

The option-critic architecture is useful for temporal questions in autonomous driving; because driving-related questions are often temporal, new questions can be generated for the subsequent actions after just several seconds. Hence, it is important to study the formulation of questioning, with research focused on the generation, organization, and evaluation of questions for transparent autonomous driving (Zablocki et al. 2022). Note also that the sensitivity of driving decisions varies dynamically in real time, creating different levels of risk for the vehicle. In general, low-risk actions and options are preferred. However, in safety stringent situations, we need to explore efficiently (possibly in real-time) to manage possible dangers. This step requires a representation of the risks in decision making with a principled way of evaluating the risks to decide which risk level the vehicle is to undertake. Experiments by (Zhang et al. 2018) showed that considering no risks but only acting according to the maximum reward principle as in traditional RL is not always the best decision and can fail to discover the optimal policy. In contrast, acting according to a variety of levels of risk can find an optimal policy in environments with a diverse range of different transition and reward dynamics. We can thus infer and conclude that decision-making for autonomous vehicles is time-sensitive, often in sub-seconds, and a well-composed question hierarchy may not only help to select the present action but also determine subsequent actions that help sustain safe driving. The hierarchical structure can also provide temporal, informative, and reliable explanations in critical traffic situations with appropriate benefits.

6. Conclusions

As a result of our ongoing study, we presented a general design framework for XAI-based autonomous driving. We validated the framework with a case study of a post-accident analysis and showed that the proposed framework could have multi-faceted benefits to autonomous driving systems. First, the concept of the intrinsic and post-hoc explanations is not only limited to providing transparency on real-time decisions but also provides further opportunities to debug, fix, and enhance existing intelligent driving systems. Moreover, we showed that the principles of the proposed framework could address three actual issues, namely, responsibility, liability, and semantic gaps in the realm of autonomous driving. Finally, we presented some XAI approaches as future work and elucidated their potential in the explainability of autonomous driving.

While the presented propositions are promising directions to follow, whether these concepts work effectively in a real driving environment remains unclear for now and is a limitation of our preliminary study. As a next step, we are performing empirical research conforming to the principles of the presented framework. Currently, we are trying to incorporate visual question answering with model-based reinforcement learning to achieve explainable vision mapped to explainable actions. Two interesting areas for deeper investigation are 1) a comparative analysis of model-free and model-based reinforcement learning approaches on the same task, and 2) whether the interpretability of an AI architecture for intelligent driving results in reduced accuracy of the interpretable algorithm compared to its original version on the same task. Therefore the contributions of this paper are mainly theoretical and further empirical studies are needed for proof of concept. We anticipate that further practical work based on these propositions can be helpful towards public acceptance of autonomous driving technology.
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