Examining the Current Decision-Making Capabilities of Self-Driving Systems

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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Introduction:

The automotive industry stands on the brink of a transformative revolution, with self-driving systems emerging as the focal point of innovation. These autonomous systems promise to enhance road safety, reduce traffic congestion, and provide greater mobility to individuals with disabilities, among numerous other benefits. Currently, the leading cause of death in the United States for those aged 1-54 is from traffic incidents (CDC, 2023). Additionally, 94% of accidents recorded by the National Motor Vehicle Crash Causation Survey (NMVCCS) were caused due to driver error (Singh, 2018). This illustrates a clear need for improvement, in terms of safety, in the world of automobiles. Advocates of autonomous vehicles (AVs) contend that this technology holds the potential to render our roads safer and cleaner compared to our current transportation systems. As we stand on the cusp of this autonomous revolution, it is imperative to examine the current decision-making capabilities of self-driving systems critically to ensure the complete safety of these vehicles.

In this paper, I argue that while Avs hold immense potential to enhance road safety and reduce environmental harm, their widespread adoption necessitates a nuanced understanding of their capabilities, limitations, and societal implications. By examining the complex interplay between technology, human behavior, and regulatory frameworks, this paper seeks to provide a comprehensive analysis of the promises and challenges inherent in the integration of autonomous systems into our transportation infrastructure. In subsequent sections, this paper will delve into the technological advancements driving the development of Avs, examining their potential to revolutionize transportation systems and reshape urban landscapes. Furthermore, it will explore the ethical and regulatory considerations surrounding autonomous driving, including questions of liability, privacy, and equity. To help with this, the Actor-Network Theory (ANT) Framework will be used in the analysis of autonomous vehicles.

The section on “Research Methods” outlines the methodologies utilized and the types of sources that are relevant to the research. Following this, the “Current Capabilities of Self-Driving Vehicles” section provides an in-depth analysis of the present capabilities of autonomous vehicles, evaluating their performance across various driving scenarios and their adherence to safety standards. The section after applies the ANT framework to the topic by examining the key actors, networks, and controversies involved. This will allow for a deeper understanding of the complexities inherent in the advancement of autonomous technology. From there, a detailed case study of Uber’s autonomous vehicle accident is presented, offering real-world insights into the challenges and ethical dilemmas associated with autonomous driving. Through this structured examination, this paper aims to provide a comprehensive evaluation of autonomous driving technology while fostering informed dialogue on the future of transportation in an increasingly automated world.

Research Methods:

The current state of autonomous vehicles can be analyzed through the lens of Actor-Network Theory, which views technology not as an isolated entity, but as a part of complex networks involving human and non-human actors (Cresswell et al., 2010). In the context of autonomous vehicles, these actors encompass not only the technology itself—but also the workers, regulators, and the broader socio-cultural and institutional environments in which they operate. Central to ANT is the concept of obligatory passage points (Rydin, 2012), which denote crucial junctures where the network’s stability and direction are determined. Utilizing ANT, I aim to employ network mapping to visualize the intricate relationships and interactions between the actors involved in the production and advancement of self-driving vehicles. This involves identifying human actors such as developers, regulators, and users, as well as non-human actors such as algorithms, sensors, and the vehicles themselves. By analyzing the relationships between these actors, including dependencies, conflicts, and alliances, I hope to gain a better understanding of the network dynamics. Furthermore, I plan to examine controversies and stabilization processes within the network, including looking at potential points of conflict and how all actors work to resolve them. To tie everything together, I also want to investigate translation processes, examining how information and intentions are shared among actors, influencing decision outcomes. This will help me understand how decisions are made within the network and how they impact the development and deployment of self-driving systems.

To examine the current decision-making capabilities of self-driving systems, I will employ a mixed-methods approach involving both qualitative and quantitative data collection and analysis methods. To begin, I plan to access relevant documents, technical specifications, and literature related to self-driving systems through online databases, academic journals, regulatory websites, and technical reports. Specific sources may include journals such as the Journal of Autonomous Vehicles and Systems, technical reports from organizations like the National Highway Traffic Safety Administration (NHTSA), and regulatory guidelines from entities like the Society of Automotive Engineers (SAE). Synthesizing and interpreting this literature provides a comprehensive understanding of the evolving landscape of autonomous vehicles and the factors influencing the decision-making processes. Subsequently, I aim to conduct a case study from an incident involving Uber's self-driving cars to get a better picture of how all the actors involved in autonomous vehicle technology interact with each other in a reallife scenario. This can help me gain valuable insights into the ethical, legal, regulatory, technological, and societal dimensions of autonomous vehicle technology.

The methodology represents a pioneering effort to bridge the gap between technology and society as the research community embarks on a journey of exploration and discovery within the realm of autonomous technologies. Through the lens of ANT and the prism of online research, I aim to uncover the decision-making capabilities within self-driving systems, paving the way for a more informed and nuanced understanding of our technological future.

Current Capabilities of Self-Driving Systems:

Background

The landscape of autonomous driving technology has been rapidly evolving in recent years, with various companies and researchers around the world working tirelessly to advance the capabilities of self-driving cars. However, determining the current state of autonomous driving is a challenging task, primarily due to the conflicting and often sensationalized information presented by the media. To help with this, SAE International has defined six levels of driving automation to help track the progress of self-driving development (USEPA, 2023). The levels are defined as:

- Level 0 – The car has no driving automation. The driver is always in full control of the car, although the car might have the ability to send safety warnings.
- Level 1 – The car has driver assistance. This means that the car can control either the speed or steering, but not at the same time. Examples include adaptive cruise control and lane assist technology.

- Level 2 – The car can control both speed and steering, but only in certain conditions. This includes when the car is in slow-speed situations, such as parking assistance.
- Level 3 – The car has "conditional automation" capabilities. The car can control the speed and steering, as well as monitor its surroundings. The driver still needs to be paying full attention while behind the wheel (ex. Traffic Jam Assist)
- Level 4 – The car is highly automated and can self-drive in normal conditions. Human drivers will need to take over in uncertain circumstances such as extreme weather.
- Level 5 – The car is fully automated. The car can drive itself in all conditions.

Currently, self-driving systems level 3 and below are widely produced, with level 4 systems gradually developing (Wang et al, 2021). Nonetheless, developing level 4 and level 5 systems presents a much greater challenge than the first three levels. So far, the decision-making capacity of self-driving systems has been based on scenario-driven and task-driven approaches that enable the car to perform specific tasks without the need for human intervention (Ulbrich et al, 2017). However, this method of development fails to achieve the ultimate goal of producing fully automated cars. The current scenario-driven concept means that manufacturers would have to come up with an infinite number of scenarios to achieve a fully automated car.

Development of Robotaxis

In the effort for full automation, level-4 robotaxis have emerged as a pioneering application of autonomous vehicle technology, particularly in urban environments worldwide. Focusing more on the United States; Waymo, Cruise, and Motional are the companies spearheading the development and deployment of these robotaxis—leveraging advanced sensors, machine learning algorithms, and high-definition mapping to attempt to navigate complex cities safely (Schneider, 2023). Currently, there are five cities in the United States where people can take a fully operational robotaxi: San Francisco, Phoenix, Los Angeles, and Las Vegas (Yang, 2024). Dozens of other cities in the US are currently testing their own robotaxi system using level-4 self-driving technology.

Despite all this promise, there have been recent setbacks for autonomous vehicles with General Motors' Cruise having to recall 950 of its robotaxis following a pedestrian collision in San Francisco occurring on October 2nd, 2023 (Kolodny, 2023). This callback underscores the ongoing challenges and limitations facing autonomous driving technology, emphasizing that full safety and reliability have yet to be achieved. Despite the extensive testing and development efforts, incidents and technical issues persist, highlighting the complexity of navigating dynamic urban environments. Cruise's collision has not been the only cause of backlash as Waymo, Zoox, and Mercedes Benz have also had their share of controversies including collisions and protests. In just the state of California, there have been a total of 687 collisions from autonomous vehicles (California DMV, 2024). While these incidents emphasize the importance of rigorous testing, validation, and continuous refinement of autonomous systems, they also serve as valuable learning opportunities to enhance the safety and performance of self-driving technology.

China has also emerged as a leader in the pursuit of producing fully automated vehicles with companies Baidu and Pony.ai leading the front. Similarly to the United States, these companies have also started to launch robotaxis in major Chinese cities such as Beijing, Shanghai, Guangzhou, etc (Cheng, 2023). Baidu through its Apollo program has made significant strides in developing autonomous driving technology and fostering collaboration within the industry. The Apollo program has facilitated partnerships with automakers, technology companies, and government agencies, accelerating the deployment of self-driving vehicles in various cities across China. Additionally, based on a survey of Chinese residents, the reception of these autonomous vehicles has also been more positive compared to the US, with positive levels of perceived usefulness and perceived ease of use (Liu et al, 2020)

These level-4 robotaxis represent a significant milestone in the evolution of autonomous mobility, marking the transition from research and development to real-world applications in urban settings. While autonomous driving holds promise for the future of mobility, the recent Cruise recalls, as well as the regularly occurring collisions, serve as a reminder of the work that remains to be done to achieve widespread adoption and public trust. As the industry continues to innovate and iterate, addressing these challenges and mitigating future risks will be paramount to realizing the full potential of autonomous vehicles and ensuring their safe integration into everyday transportation networks.

Application of ANT Framework to Autonomous Vehicles

In this rapidly evolving landscape of autonomous vehicle technology, the assessment of decision-making capabilities within self-driving cars stands as a pivotal focus of research and scrutiny. As stated earlier, ANT provides a compelling lens through which to analyze the intricate network of self-driving systems, emphasizing the agency and interdependencies of both human and non-human elements.

Human Actors

To start, researchers and engineers are actively involved in studying and developing the decision-making algorithms and systems within self-driving cars Their expertise in machine learning, artificial intelligence, and robotics contributes to the refinement and improvement of these capabilities. They conduct experiments, analyze data, and develop new algorithms to enhance the decision-making process of autonomous vehicles (Ahmed, 2018). Additionally, government agencies and policymakers play a crucial role in shaping the regulatory landscape surrounding autonomous cars. They develop guidelines, standards, and regulations that govern the testing, deployment, and operation of autonomous vehicles. The United States Department of Transportation (USDOT) has developed an "Automated Vehicles Comprehensive Plan" which defines three goals to achieve the USDOT's vision for Automated Driving Systems (ADS) (USDOT, 2021). Next, ethicists also play a role in the network. They engage in discussions about the moral and ethical considerations inherent in self-driving car decision-making. They explore questions related to liability, accountability, and the ethical dilemmas faced by autonomous vehicles in various scenarios. In general, they work to figure out what to prioritize when it comes to ensuring the safety of the public (Nyholm & Smids, 2016). Lastly, human drivers and pedestrians remain active participants in the transportation ecosystem. Their behaviors, reactions, and interactions with autonomous vehicles shape the development and testing of decision-making algorithms. Understanding human factors is crucial for designing algorithms that can anticipate and respond to unpredictable situations on the road.

Non-human actors

At the core of the autonomous vehicle ecosystem are the self-driving cars themselves. Firstly, the decision-making capabilities of autonomous vehicles rely heavily on software algorithms. These algorithms interpret sensor data process information, and generate commands for vehicle control, including steering, acceleration, and braking. The development and refinement of these algorithms are crucial for enhancing the safety, efficiency, and reliability of autonomous vehicles (Levinson et al, 2011). Next, sensor technologies such as lidar, radar, cameras, ultrasonic sensors, and GPS enable self-driving cars to perceive their surroundings and gather real-time data about the environment. Lidar (light detection and ranging) sensors emit laser pulses and measure the time it takes for the pulses to return after reflecting off objects in the environment. This is particularly effective for detecting obstacles, identifying lane markings, and mapping the surrounding terrain. Radar (radio detection and ranging) sensors use radio waves to detect objects and measure their distance, speed, and direction of travel. This is useful in adverse weather conditions such as rain, fog, and snow, where visibility may be limited for other sensor technologies. There are also cameras that capture visual information from the surrounding environment including road signs, traffic lights, pedestrians, and other vehicles. Combining this with deep learning algorithms allows the car to identify and classify objects, recognize road markings, and interpret complex traffic scenarios (Marti et al, 2019).

In addition to the technical non-human factors, the self-driving car network includes regulatory frameworks and infrastructure elements. Regulatory frameworks established by government agencies and policymakers govern the development, testing, deployment, and operation of self-driving cars. These regulations define safety standards, licensing requirements, and liability frameworks for AVs. In the United States, there are both federal and state actions that have taken place dealing with laws related to self-driving vehicles (NCSL, 2020). Lastly, infrastructure elements such as traffic lights, signs, road markings, and communication systems interact with self-driving cars and influence their decision-making processes. Connected infrastructure technologies enable vehicle-to-infrastructure (V2I) communication, providing additional information and enhancing the capabilities of autonomous vehicles in navigating complex environments (Dey et al, 2016).

Interaction of Actors

Self-driving cars operate within socio-technical networks characterized by dynamic relationships and dependencies among human and non-human actors. The human and non-human actors described in the sections above engage in interactions that shape the design, testing, and evaluation of the decision-making capabilities of autonomous vehicles. For example, manufacturers collaborate with researchers and engineers to develop and optimize decision-making algorithms. Regulators and policymakers work alongside industry stakeholders to establish safety standards, certification processes, and legal frameworks governing autonomous vehicle technology. We can see these relationships further in a case study of an incident involving Uber's autonomous vehicle program.

Case Study: Uber's Autonomous Vehicle Incident

Background on Incident

On March 18th, 2018, an Uber self-driving taxi struck and killed a pedestrian in Tempe, Arizona, prompting significant scrutiny of the safety and efficacy of autonomous vehicle technology. The subsequent investigation by the National Transportation Safety Board (NTSB) not only highlighted the technical failures, but also revealed complex interactions and power dynamics within the autonomous vehicle network. The incident also exposed gaps in Uber's safety culture, revealing a network where internal milestones and initiatives took precedence over safety considerations (NTSB, 2019).

At the heart of the incident was the Uber backup driver who failed to effectively monitor the road and the automated driving system, leading to the tragic outcome. The backup driver pleaded guilty to endangerment and was sentenced to three years of supervised probation (CNN, 2020). There was also further investigation into the technical failures and sensor limitations that may have contributed to the accident. Research was conducted into the effectiveness of Uber's sensor suite, including lidar, radar, and cameras, in detecting and responding to pedestrian movements and other objects on the road. According to the NTSB report, the system detected an object six seconds prior to the crash; however, the system first classified the pedestrian as an unknown object, then as a vehicle, then lastly as a bicycle. Due to the variability of the classification, the predicted path of the pedestrian was faulty, and it was not until 1.3 seconds before the collision that the system determined that emergency braking was necessary. However, the emergency braking was designed so that only the operator could use it, so the car was unable to slow down, going 39 miles per hour when it ran into the pedestrian. The accident occurred at nighttime, which could have impacted the performance of the sensors; although, Uber reported that the radar and lidar technology were effective at identifying, especially in the darkness (Kohli & Chadha, 2019).

In the aftermath, Uber ceased testing of its self-driving vehicles to examine the safety concerns and reevaluate their autonomous vehicle program. This decision to suspend testing was aimed at ensuring the safety of pedestrians, cyclists, and other road users while the company conducted a thorough investigation into the incident (Said, 2018). It was not until the end of 2018 that Uber resumed its testing of autonomous vehicles. Unfortunately for Uber, the damage was done with the accident as their autonomous vehicle program was never able to get back on its feet. In a later report made by the National Transportation Safety Board (NTSB), it was said that Uber's "inadequate safety culture" contributed to the fatal collision. The NTSB Chairman, Robert Sumwalt, stated "Safety starts at the top, the collision was the last link of a long chain of actions and decisions made by an organization that unfortunately did not make safety the top priority" (NTSB, 2019). The report exposed Uber's tendency to take safety shortcuts to fulfill internal milestones and initiatives. Ultimately, Uber discontinued its autonomous vehicle program in 2020 as they were never able to regain their footing after the tragic incident.

Applying Actor-Network Theory (ANT) Uber's Incident

Human actors are at the forefront of the incident. Developers, represented by Uber, aim to advance autonomous vehicle technology for commercial purposes, driven by the promise of innovation and profit. This includes engineers, data scientists, and investors, who contribute expertise and resources to develop and deploy self-driving vehicles. Regulatory and policymaking entities, such as the NTSB and local transportation authorities, serve as critical actors in the network, advocating for safety, accountability, and public welfare. They try to enforce the adherence to safety standards, certification processes, and liability frameworks to ensure the safe integration of self-driving cars into society. There are also ethicists and advocacy groups that highlight ethical considerations and raise awareness about the potential risks and implications of autonomous vehicles. They attempt to push for greater transparency, accountability, and ethical decision-making in the development of self-driving technology.

Beyond human actors, non-human elements such as sensor technologies, machine learning algorithms, and software systems play an important role in shaping decision-making processes within autonomous vehicles. Lidar, radar, cameras, and other sensors serve as the sensory organs of self-driving cars. However, they may encounter limitations in accurately detecting and responding to dynamic environmental stimuli, as evidenced by the misclassification of the pedestrian in the Uber incident. Machine learning algorithms also contribute to the decision-making capabilities of self-driving cars, processing sensor data and generating commands for vehicle control. Yet, the effectiveness of these algorithms relies on extensive training data and ongoing refinement, posing challenges in anticipating and responding to novel or unforeseen scenarios on the road.

The Uber incident exemplified how all the actors described can interact with each other and their power dynamics. While developers sought to innovate and commercialize autonomous vehicle technology, regulators advocated for safety and accountability, resisting unchecked advancement. In the aftermath of the incident, regulatory networks like the NTSB asserted their influence by demanding transparency from Uber. The NTSB’s investigation and subsequent reports shed light on Uber’s safety shortcomings, exposing a network characterized by insufficient monitoring of backup drivers and inadequate risk assessment procedures. This scrutiny prompted Uber to suspend testing and reevaluate its autonomous vehicle program.

Discussion:

The development and integration of AVs has presented many challenges and opportunities, demanding careful consideration of regulatory frameworks, technological advancements, and societal implications. While the landscape of AVs is marked by innovation and promise, it is also filled with complexities and uncertainties, requiring proactive measures to ensure safety, accountability, and public trust. Amidst all the complexities, it is imperative to recognize that safety should be paramount. The incidents involving Cruise and Uber underscore the need for stringent regulatory oversight and safety standards that mitigate risks and protect public welfare. However, regulatory efforts should strike a balance between fostering innovation and safeguarding against potential harms, avoiding overly restrictive policies that limit technological progress.

To address the challenges posed by AVs, policymakers must develop comprehensive regulatory frameworks that define safety requirements, certification processes, and liability frameworks. These regulations should be adaptable to evolving technological advancements while making sure developers are accountable for safety standard violations. Policymakers should also incentivize collaborative research and development among industry leaders, academic institutions, and government agencies. As of right now, it feels like each party are working separately to see who achieves full automation first. As we can see from the case study, this can be counter-productive and lead to potential harm. By fostering interdisciplinary collaboration, we can have diverse viewpoints, which helps to address complex challenges in AV technology. Additionally, policymakers should invest in public education and engagement initiatives to increase awareness and understanding of self-driving technology. This can address public concerns and build public trust. If AVs are going to be a big part of our future, we should be educated on their capabilities and shortcomings.

For the future, more research is needed to continue to advance technological innovations in AVs. Sensor technologies and decision-making algorithms have fallen short so far, leading to repeated incidents involving self-driving cars. By enhancing the reliability and robustness of these systems, researchers can minimize risks and enhance safety and autonomous transportation. Additionally, more research is also needed to improve public trust of AVs. The current perception from the public is a bit skeptical due to common collisions and accidents. Understanding user preferences and behaviors can inform the design and deployment of autonomous vehicles that align with user needs and expectations.

Conclusion:

The emergence of autonomous vehicles promises a shift in the landscape of transportation by enhancing safety, efficiency, and accessibility. However, all this promise also comes with its challenges. The presence of incidents such as those from Uber and Cruise highlight the importance of stronger regulatory frameworks, tighter safety standards, and further research to address technological limitations and societal concerns. As we continue to navigate the complexities of self-driving vehicles, proactive measures are essential to ensure safety, accountability, and public trust. In conclusion, the journey towards fully autonomous transportation has provided hope for transformative innovation but has also proven to be problematic. However, by leveraging interdisciplinary insights, embracing ethical considerations, and prioritizing public welfare, instead of chasing profit, we can harness the potential of autonomous vehicles to create a safer, more sustainable future of mobility for all.

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