Anomaly Detection Through Explanations

by

Leilani Hendrina Gilpin

B.S., University of California, San Diego (2011)
M.S., Stanford University (2013)

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Author ....
Department of Electrical Engineering and Computer Science
August 28, 2020

Certified by...
Gerald Jay Sussman
Panasonic Professor of Electrical Engineering
Thesis Supervisor

Certified by...
Lalana Kagal
Principal Research Scientist in CSAIL
Thesis Supervisor

Accepted by ....
Leslie A. Kolodziejski
Professor of Electrical Engineering and Computer Science
Chair, Department Committee on Graduate Students

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Abstract

Under most conditions, complex machines are imperfect. When errors occur, as they inevitably will, these machines need to be able to (1) localize the error and (2) take appropriate action to mitigate the repercussions of a possible failure. My thesis contributes a system architecture that reconciles local errors and inconsistencies amongst parts. I represent a complex machine as a hierarchical model of introspective subsystems working together towards a common goal. The subsystems communicate in a common symbolic language. In the process of this investigation, I constructed a set of *reasonableness monitors* to diagnose and explain local errors, and a system-wide architecture, *Anomaly Detection through Explanations* (ADE), which reconciles system-wide failures. The ADE architecture contributes an explanation synthesizer that produces an argument tree, which in turn can be backtracked and queried for support and counterfactual explanations. I have applied my results to explain incorrect labels in semi-autonomous vehicle data. A series of test simulations show the accuracy and performance of this architecture based on real-world, anomalous driving scenarios. My work has opened up the new area of explanatory anomaly detection, towards a vision in which: complex machines will be articulate by design; dynamic, internal explanations will be part of the design criteria, and system-level explanations will be able to be challenged in an adversarial proceeding.

Thesis Supervisor: Gerald Jay Sussman
Title: Panasonic Professor of Electrical Engineering

Thesis Supervisor: Lalana Kagal
Title: Principal Research Scientist in CSAIL

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"You can do it, only you can do it, you can't do it alone."

– Patrick Henry Winston

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Chapter 1

Introduction

Complex machines, like all things, are imperfect. Testing and proving properties can harden these systems, but they are inadequate–it is impossible to test all failure modes. Consider a human crossing the street. It is considered "safe", if you look both ways and do not detect an oncoming vehicle. But this protocol does not include the 6.25×10^{-7} chance of being struck by a local meteorite, asteroid, or comet impact[1]. Instead of building provable test cases, my research is a complementary approach: I work on the methodologies and underlying technologies of monitoring architectures that can mitigate underlying system failures.

Society has built reasonably stable structures to minimize the occurrence and the consequences of bad human behavior. One such mechanism is a human organization: where each kind of work that is to be done is given to a committee of personnel who work together on said task. Another mechanism is the legal system. It enforces the minimal norms of the society, subject to a set of rules. The legal system investigates reports of bad behavior after-the-fact, or *ex post facto*, and takes action to mitigate and to prevent the recurrence of that behavior through an investigation. This investigation is dependent on evidence: stories recounting the bad behavior and explanations from the alleged bad actor. Currently, complex machines do not have the ability to provide this sort of evidence (without substantial effort).

[1]In 2014, Professor Stephen A. Nelson calculated the lifetime odds of dying from a local meteorite, asteroid, or comet impact as 1 in 1,600,000: `http://www.tulane.edu/~sanelson/Natural_Disasters/impacts.htm`

For complex machines to be robustly intelligent, they *must* keep internal reports of their behavior. I decompose a complex machine into an organization of subsystems working towards a common goal: an *architecture*, similar to human committees. The architecture is able to detect and reconcile local failures (within a committee), as well as inconsistencies amongst subsystems using explanations as a *technical language*. An explanation synthesizer produces an argument tree, which can in turn produce counterfactual explanations for an adversarial proceeding. The synthesizer depends on the underlying subsystem's ability to tell its own coherent story about the reasons for its decisions or actions.

Some subsystems are so opaque (e.g., deep neural networks) that there may be no way to explain the subsystem's behavior. Perception is an example. In self-driving cars, there may be a vision system interpreting images from an optical camera. Computer vision systems are susceptible to be fooled [170] and lack commonsense[2]. If a vision system reports that it observes a mailbox walking across the street [79], that is clearly not possible. If it observes an elephant in the sky, that does not make sense. Labeling the same object as three very different things at the same time (e.g., a vehicle, an unknown object, a bicycle) is unreasonable[3]; that is a confused judgement that should be discounted. To combat these types of nonsensical judgements, I developed a reasonableness monitor [73], which supplements opaque decision making with rules, an ontology, and commonsense knowledge. With the addition of a reasoner, the reasonableness monitor produces a judgement of reasonableness and an explanation supporting that judgement. I present the technical details of this local commonsense sanity check in Chapter 4. I extended the end-to-end reasonableness monitor into an adaptable framework [78] that can impose sanity checks on *all subsystems* of a complex machine. This includes sensory LiDAR[4], after applying a sensor interpreter, which I present in Chapter 5.

[2]The "AI" in a self-driving vehicle mistakes woman on bus for jay-walking: `https://slashdot.org/story/18/11/26/0527259`

[3]This labeling scenario actually happened in the Uber self-driving car accident in 2016 [180].

[4]LiDAR is the commonly used acronym for Light Detection and Ranging. It is a sensor that uses light from a pulsed laser to measure distance from the source point. The aggregated detections from several light pulses form a point cloud.

Complex machines also lack internal communication. When the underlying parts disagree, they cannot justify their behavior. In the Uber self-driving vehicle accident[5], an unresolved disagreement among parts lead to a pedestrian fatality [180]. In summary, the vision system perceived an oscillating label where the pedestrian was located, although the LiDAR system detected a moving object in that region. The mechanism for combining this information chose to ignore the object. Instead, I created a system-wide explanatory monitoring architecture, *Anomaly Detection Through Explanations* (ADE). The architecture consists of local reasonableness monitors around subsystems, constructed into a system hierarchy, similar to how human organizations are structured. An explanation synthesizer reconciles disagreements. In the Uber example, the synthesizer is able to validate the vision system's *detection* of an object, while discounting the oscillating *labels* of that object, because they are inconsistent. The synthesizer constructs a reason *why*, by examining the explanations from the underlying subsystems that support the judgement. The ADE architecture is presented in Chapter 7.

Explainability under uncertainty, which can learn from explained failures in dynamic situations, is an unexplored area. Explanatory artificial intelligence (XAI) has become a popular research agenda under the DARPA XAI program [88] and the EU's GDPR on the "right to explanation" [84]. Although, it is not without criticism [193]: explanatory systems are all explaining different processes, lacking common evaluation metrics [76] and intervention mechanisms. Instead, the majority of explanatory tools are after-the-fact analysis tools, like the model-based, qualitative reasoning explanation generation method presented in Chapter 3. This approach is similar to the sensor-data interpreter in Chapter 5, in which raw sensor data is translated into a (mostly symbolic) list of descriptions.

I contribute a *common language* for reconciling system-wide failures. The pieces of a complex machine report their state at various levels of detail: the vision subsystem reports high-level labels, and the sensors output low-level log traces. By

[5]Uber self-driving car ignores objects: `https://www.theinformation.com/articles/uber-finds-deadly-accident-likely-caused-by-software-set-to-ignore-objects-on-road`

producing explanations of their behavior, the subsystems are able to speak the same language, argue amongst themselves, and use these explanations to support or challenge high-level decisions. These monitoring pieces may have different conclusions; they may directly conflict and contradict each other. But since the monitors are constantly inspecting the behavior of their neighboring subsystems (and themselves), the explanations are *dynamic*. They can be augmented, changed, and challenged with alternative context, more evidence, and in different scenarios. For example, with various weather sensor information, the LiDAR monitor's explanations can become stronger or weaker, since LiDAR is unreliable in rain, fog, or snow[6]. A formerly strong LiDAR monitor explanation can be weakened by this information, encouraging the other sensors and subsystems to reevaluate their explanations. A series of test scenarios demonstrating this kind of dynamic behavior are in Section 7.5.

Some of the most compelling applications of this work include people: shared autonomy, social structures, government structures, and others, which are elaborated in Chapter 8. But whether humans are involved is irrelevant. My methodologies monitor every subsystems' behavior, even if one or more of the subsystems is a human!

I argue that the novel use of explanations is for the machine itself, which is a novel perspective compared to previous work [88]. My thesis enables complex machines to reason about new scenarios, even if they have not seen that circumstance before. The current successes of autonomous vehicles are completely dependent on their ability to learn through (previously observed) experiences [243]. Instead, I model an autonomous vehicle as committees of introspective subsystems working together towards a common goal. This results in a self-explaining architecture, where autonomous vehicles can reason and explain the ever-growing, long tail of failures in real-world environments[7].

[6]LiDAR is unreliable in certain weather conditions: `https://www.draper.com/news-releases/new-lidar-detector-enables-self-driving-cars-see-sun-rain-fog-and-snow`

[7]Errors and failures are different kinds of bugs. The Hacker's Dictionary defines a "bug" as "an unwanted and unintended property of a program or piece of hardware, especially one that causes it to malfunction." An error is a technical property. Most errors are harmless, such as an "undesirable" search query results, or a typo. A failure is an error with consequences. A failure occurs when there is a difference from the expected result. In self-driving cars, failures can be fatal. I work on explaining system-wide *failures* and detecting local *errors*.

1.1 Definitions

My dissertation contributes a local error detection monitor, and a system-wide failure detection architecture. The output of the monitor is a justification of unreasonableness, and the output of the architecture is an explanation. I define the following key terms to be consistent with the IEEE software engineering literature [100], using the running example of an off-by-one error[8].

1. An *error* produces an incorrect internal state [100]. For example, an off-by-one error that changes a location outside of memory, where no one cares about that location, is just an error. I detect and justify *local subsystem errors*.

2. A *failure* is an "external, incorrect behavior with respect to the expected behavior (observed)" [100]. A failure has consequences. Consider an off-by-one error that clobbers a location whose value is essential to a safety-critical process–that is a failure. I detect and explain *system-wide failures*.

My thesis contributes methods that *explain* themselves and *justify* their behavior.

1. A *justification* is a description of whether something is right or reasonable (or not). Reasonableness monitors (in Chapter 4) provide justifications supporting an unreasonable or reasonable judgement of an intended subsystem behavior.

2. An *explanation* is a justification that *also* describes the causes, context, and/or consequences of an error, failure, or stable system state. An explanation answers "why questions" (see Section 8.1.1).

1.2 Thesis Contributions

I use symbolic internal subsystem representations, or *explanations*, to enable complex machines to introspect, reason, and reconcile their own failures. I contribute to

[8]An off-by-one error (OBOE, OBO, OB1 and OBOB) is a logic error in computer programming. It typically occurs when an iterative loop iterates one too many or one too few times. It can also occur due to an incorrect inequality symbol ($<$ instead of $\leq$ or $>$ instead of $\geq$ and vice versa), or due to array indexing, in which the programmer mistakes that an array starts at 0 instead of 1 (and vice versa).

three technical aspects of an introspective system: local sanity checks, system-wide communication, and explanation feedback. While my dissertation focuses on the domain of self-driving cars, the methodologies are applicable to any complex machine that is composed of multiple parts.

1.2.1 Local Sanity Checks

Complex machines can fail in two distinct ways. One type of failure could be localized to a specific subsystem. Most local failures are due to flaws that a human would never make. In order to provide the individual subsystems of this complex machines with a last-pass "reasonableness" check, I developed a commonsense monitoring system: reasonableness monitors. Reasonableness monitors process the output of a (possibly opaque) subsystem and use a set of rules, ontology and commonsense knowledge leading to a judgement and justification of reasonableness.

1.2.2 System-wide Communication

The second type of complex machine failure is due to flawed communication amongst subsystems. There is limited internal communication in complex machines: the underlying subsystems perform tasks at different levels of abstraction, therefore reporting their decisions, states, and world views in different forms of communication. To provide a common language for subsystem communication, I implemented a system architecture: Anomaly Detection Through Explanations (ADE), that can reconcile subsystem inconsistencies in a common explanation language. A series of test simulations show the accuracy and performance of this architecture based on simulated, anomalous driving scenarios.

1.2.3 Explanation Feedback

Explanations should make complex machines work better. I show how explanations can be fed back into a monitoring architecture to improve decision making with a "rule learning" prototype method. Test simulations on a real robot, in Section 6.3.2, show that explanations can be used to explore new environments and learn reasonable behaviors.

1.3 Thesis Overview

Chapter 2 positions this thesis in the context of related research in the methodologies and underlying technologies related to anomaly detection, knowledge representation, explanation[9], and introspection.

- Chapter 3 describes an ex post facto model-based reasoning methodology to explain and summarize vehicle logs post accident.
- Chapter 4 introduces reasonableness monitors: a local sanity check that supplements decisions with commonsense reasoning and rules.
- Chapter 5 describes a sensor interpreter to produce qualitative descriptions from LiDAR traces.
- Chapter 6 introduces an algorithm for incorporating feedback into an explanatory monitor.
- Chapter 7 describes Anomaly Detection through Explanation (ADE): a system-wide architecture that can reconcile inconsistencies amongst subsystems.

Chapter 8 reviews and defines the types of machine explanations that important to society. I also discuss the *ethical* implications of artificial intelligence, and argue that explanations can mitigate societal fears of intelligent machines. I conclude in Chapter 9 by reviewing the contributions of this dissertation, and proposing future research directions and applications.

[9]In Chapter 8, I exclusively review the eXplanatory artificial intelligence (XAI) literature, including *recommendations* for societal explanations.

Chapter 2

Background

"A lot can go wrong when we put blind faith in big data."

– Cathy O'Neil

In this chapter, I provide a literature review of relevant work in anomaly detection, diagnostics, knowledge representation and reasoning, and multi-agent systems. I also review previous work on integrating perception and reasoning, which is a motivating application of my thesis work.

In subsequent chapters, I review the specific components of self-driving vehicles. I review research ideas from the philosophy literature in Chapter 8.

2.1 Anomaly Detection

Anomaly detection is a data mining process that finds rare or mysterious instances. It is used to identify fraud [143], intrusion [130], and event detection in sensor networks [4]. In machine learning, when there is a large amount of *training data* available, these methods are either "supervised" (the training data has labels of anomalous or non-anomalous) or "unsupervised" (the training data does not have labels). The majority of machine learning methods for anomaly detection are unsupervised, so that methods look for instances outside of the distribution and/or trends in the training data. The most popular and successful of these unsupervised methods include density-based techniques that detect outliers by clustering together *similar* points. This includes k-nearest neighbor [118, 139, 10], local methods [28, 202, 45], cluster-analysis detection [94, 34] and isolation forests [141, 142].

Similar approaches have been proposed for high-dimensional data [260], where there are so many dimensions of the data, that it may be unscalable to cluster (or group) similar data points together. When the data is too large or high-dimensional to process at once, some methods project the data onto a subspace [121, 108], or use tensor processing techniques [59], or interpret correlations [123]. Anomaly data may also be available as a graph, which leads to a multitude of graph-based techniques [5].

Other approaches detect anomalies by creating scores or formulas that can point to "atypical" data points or events. One score is an "interestingness" score [71], which is regardless of the kind of patterns being mined. More precise logic-based techniques can find anomalies that do not satisfy some predicate for *typical behavior*. In real-world environments (driving, robotics, network intrusion, etc.) the exact claims may not be precise. Therefore less precise, approximate reasoning like fuzzy logic [36] allows inference on less well-defined topics.

And if there is a multitude of data, processing power, and models available, ensemble techniques combine multiple models for better anomaly detection results [258, 259]. This includes feature bagging [131, 171] to find the features most correlated to fraud, or score normalization [122, 201].

2.1.1 Diagnostics

In model-based reasoning, anomaly detection is referred to as diagnostics. In diagnostics, it is assumed that there is little or no training data, and so finding errors aligns with detecting "symptoms" that align with an expert model. This is performed with either consistency-based diagnosis [188, 52] that finds diagnoses that are consistent with symptoms. Or detecting novel faults by suspending constraints [48, 70], which makes no presumption about faulty subsystem behavior.

2.1.2 Monitoring

In diagnostics, monitoring is used around plans (or goal states) and components to anticipate failures. In a multi-step execution plan, causal-link monitoring consistently checks rules and preconditions once the desired output is established for each step, where these causal links can be qualitative [51] and input back into qualitative reasoning systems. If the monitoring system is examining actions, then action monitoring can verify preconditions right before specific actions are executed, this is typically done in RosPlan [35].

Once a symptom is detected, a system may want to repair itself. These types of self-configuring [236] systems have a flexible representation that needs to uphold some consistent design choices and principles. A self-configuring system may focus on reconfiguring components modes [235], or have a meta-process that selects between program choices [114] .

2.2 Knowledge Representation and Reasoning

A goal of my work is to create self-explaining mechanisms that are flexible and adaptable. This relies on using flexible representations of data, inspired by frame-based representation, a formal ontology to reason about high-level concepts, and various reasoning approaches that cater to multiple types of data. My research is focused on representations that cater to *uncertainty*.

2.2.1 Frame-based Representations

Frames [157] are a typically symbolic representation that enable a system to reason easily. Frames were derived from semantic networks [183], as a way to represent memories and knowledge, especially for language. This extended into representing language as these sorts of trans-frames or scripts [199], which reduced search space and memory. This type of representation relies on a structure in subsumption hierarchies like `IsA` [27] or a structured ontology.

2.2.2 Ontology

An ontology an organization of a concept (or domain) into relations: how different concepts are related to the target concept. An ontology is a specification of a shared conceptualization. Domain ontologies are specific to an application or domain, whereas "upper" ontologies are domain-independent, more prevalent for the semantic web [22] including the Web Ontology Language (OWL) [13], Friend of a Friend (FOAF) [29], and Yago [216]. Some upper ontologies are the basis for commonsense knowledge bases [57, 155].

2.2.3 Commonsense Knowledge and Reasoning

Commonsense knowledge is difficult to define. In the simplest terms, commonsense knowledge consists of facts about the everyday world that are self-evident; for example "lemons are yellow" or "animals can move." Commonsense knowledge bases [135, 212, 62] provide these sorts of intuitive statements. Whereas commonsense reasoning models the human process of using these statements to solve problems, like the Winograd Schema challenge [137]. Other more formal approaches [163] use "event calculus" to reduce commonsense reasoning to first-order logic approaches.

2.2.4 Reasoning

In addition to commonsense reasoning, other types of classical reasoning approaches cater well to finding anomalies. Hypothetical reasoning [98] is an extension of abductive reasoning [175], in which a hypothetical is deemed plausible by verifying each of its logical consequences. Another approach to reasoning about uncertainties is to look at analogies [72]: an inductive reasoning process that examines similar concepts to understand new concepts. If we consider that humans understand new circumstances by examining stories, then story-understanding [240] can be applied to understand new scenarios in complex machines.

2.2.5 Cognitive Architectures

The types of mechanisms that I present in this thesis are complex cognitive architectures. Cognitive architectures, first coined by Allen Newell [167], aim to understand human intelligence by mimicking the human reasoning process in a computer model. An implementation of a cognitive architecture is SOAR [125], which is still prevalent today. Society of Mind [158] is a theoretical framework for a cognitive architecture, along with its successor, The Emotion Machine [160], which incorporates ideas from theory of mind.

2.2.6 Theory of Mind

Theory of mind, or using insights from one's thought-processes to understand that of others is an important theory for anticipating behavior [7]. This is especially important to anticipate complex situations [117], which are prevalent in the self-driving vehicle domain.

2.3 Multi-agent Systems

Multi-agent systems [218] are a complex system, which are composed of multiple interactive agents. This is similar to my *organizational approach* of a complex system as being made of multiple subsystems that interact via *explanations*. Another variant of multi-agent systems is modeling collective behavior [232], where the observed environment is used to construct rules for a decentralized system of robots.

2.4 Integrating Perception and Reasoning

The integration of perception, recognition, and higher reasoning capability is a hallmark of human intelligence modeling–from Gestalt psychology [153] and early machine vision systems [190, 228] to cutting-edge standardized models of human cognition [124]. Human cognition integrates perception and "pure" object recognition with reasoning and symbolic manipulation. Humans are able to process sensory inputs both “top-down” and “bottom-up”[1]

Some cognitive theories emphasize the influence of symbolic processes on perception. Scientific evidence supports the view that normal perceptual experiences may rely more on knowledge than modes of sensation [226]. Winston’s [239] “inner” language hypothesis says that humans construct complex symbolic descriptions of situations, knowledge, and events; enabling humans to understand the world and problem solve[2]. The development of reasonableness monitors is devoted to integrating subsystems that represent the “inner”, physical, non-linguistic representation and reasoning domains of mental models [103] and imagery [176] that are theorized to be distinct from humans’ “outer” language of familiar lexical items and linguistic forms.

[1]A top-down processing approaches starts from the general and moves to the specific. A bottom-up processing approach starts from the specific and moves to the general.

[2]The strong story hypothesis inspired the idea of “story-enabled intelligence”: systems that can recount their own story “exhibit intelligence of a higher order.” `http://logical.ai/story/`.

Chapter 3

Ex post facto Explanations

"...an adequate account that tells us all we want to know about explanations in general must wait until prior problems have been solved."

– Sylvain Bromberger in *On What We Know We Don't Know* [30].

When autonomous systems malfunction, different stakeholders require a diagnosis of the failures that led to the malfunction. For example, when autonomous vehicles get into fatal accidents, as in the Uber self-driving car accident[1], it is important to diagnose why the malfunction occurred quickly and precisely. When an accident happens in a car that is co-driven by a person and a machine, police officials, insurance companies, and the people who are harmed will want to know who or what is accountable for the accident. In this chapter, I present a methodology to analyze and understand vehicle logs *after-the-fact*.

I present two model-based reasoning systems, which are initialized with measured data from a simulation environment. The qualitative mechanical model diagnoses specific mechanical component failures. The semi-qualitative physics model diagnoses unusual physical forces on the vehicle, which can lead to erratic driving behavior. The models are able to abstract information from data to produce concise and understandable explanations of vehicle actions–a summary that is simple enough for users

[1]A self-driving Uber test vehicle struck and killed a pedestrian in March 2018 [151]. For more cases, refer to this dynamic list of self-driving vehicle fatalities: `https://en.wikipedia.org/wiki/List_of_self-driving_car_fatalities`

to understand. This chapter was previously published as a conference proceeding [75].

3.1 Introduction

Modern automobiles are highly sophisticated, complex, and interconnected electromechanical systems. However, the existing tools for signaling errors are imprecise. For example, the “check engine” light indicates the plausible existence of problems without providing any justification.

As society moves towards semi-autonomous and, ultimately, fully autonomous vehicles, there is a need for vehicles to be capable of producing explanations of their behavior and internal state. These explanations will help in performing maintenance, analyzing driver behavior, and determining accountability for problematic actions. With the addition of sensors and software, pinpointing problems–even simple ones like low tire pressure, becomes difficult; due to the increased range of potential causes. In semi-autonomous driving, understanding the relative contributions of humans and/or mechanisms to an unwanted event, like a car accident, will be important for failure analysis and determination of accountability. Creating the ability for an autonomous agent to provide a coherent explanation of its own behavior is an essential prerequisite to building the necessary trust and confidence in such agents. If autonomous agents cannot reason about their decisions, then they will not be able to correct themselves, especially when things go wrong. This chapter explores the development of a methodology for developing *ex post facto*, i.e., after-the-fact, explanations from vehicle logs.

3.1.1 Definition of Vehicle Specific Components

When I refer to “vehicle” logs, I am referring to a Controller Area Network (CAN bus) log. This internal network of the vehicle is decentralized: it allows Electronic Control Units (ECUs), the embedded controller of one or more of the electrical systems or subsystems in a vehicle, and devices to communicate their state amongst each other without a host computer. These communications are recorded on a CAN bus log, which is mimicked in the simulated CAN bus log. For each ECU component, a "snapshot" is recorded at each time stamp. This includes the CAN bus code and "parameter information," which varies between ECU components. For the braking ECU, it is binary: 0 (brakes not engaged) or 1 (brakes engaged). But for other ECUs, like drive mode or wheel speeds, the parameter information is a list. The difficulty is providing a *common language* to process these parameters into a meaningful, symbolic story.

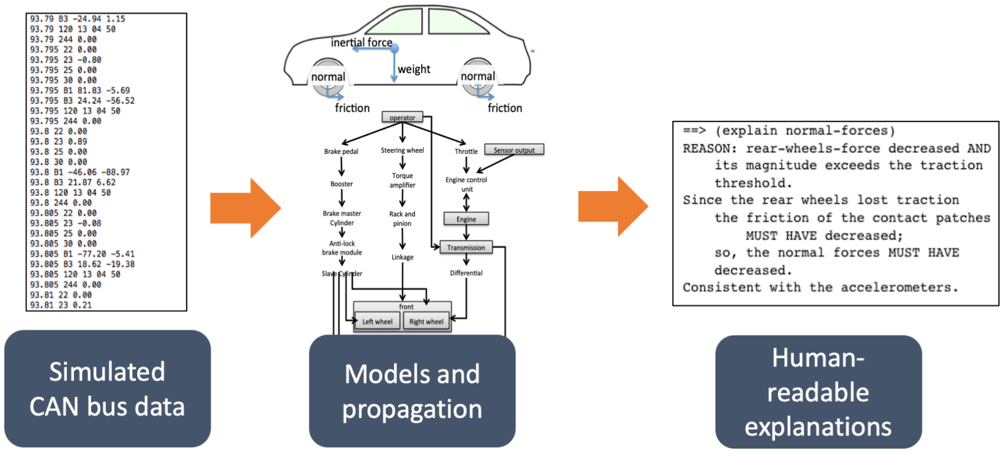
Since the CAN bus logs record ECU data at various levels of detail, I processed and represented CAN bus data in terms of qualitative descriptions. These qualitative descriptions, e.g., `inc` (increasing) or `dec` (decreasing), are a description of the first derivative change. In Section 3.2.2, I define an extended definition of qualitative terms based on the qualitative algebras first proposed by Johan de Kleer [49]. I apply abductive reasoning: I start from an observation or result to deduce the likely explanation for the observations, using a model of the vehicle system to find (mis)behaviors. My method provides understandable, symbolic, simulated vehicle log descriptions.

3.2 Method Overview

My system is a three-component process and methodology. The system is visualized in Figure 3-1.

1. Data processing produces "intervals of interest," in Section 3.2.1.
2. Models describe the *expected behavior* of the underlying vehicle system, in Section 3.2.3. The models are initialized with "intervals of interest."
3. Reasoning explains an "interval of interest" by running the models, and examining the outputs and dependencies in Section 3.2.7.

I applied this methodology to a simulated vehicle. I show a series of test simulations that show the ability of the methodology to explain skids in Section 3.3. In the next sections, I review the technical specifications and artifacts.



```
93.79 B3 -24.94 1.15
93.79 120 13 04 50
93.79 244 0.00
93.795 22 0.00
93.795 23 -0.80
93.795 25 0.00
93.795 30 0.00
93.795 B1 81.83 -5.69
93.795 B3 24.24 -56.52
93.795 120 13 04 50
93.795 244 0.00
93.8 22 0.00
93.8 23 0.89
93.8 25 0.00
93.8 30 0.00
93.8 B1 -46.06 -88.97
93.8 B3 21.87 6.62
93.8 120 13 04 50
93.8 244 0.00
93.805 22 0.00
93.805 23 -0.08
93.805 25 0.00
93.805 30 0.00
93.805 B1 -77.20 -5.41
93.805 B3 18.62 -19.38
93.805 120 13 04 50
93.805 244 0.00
93.81 22 0.00
93.81 23 0.21
```

```
==> (explain normal-forces)
REASON: rear-wheels-force decreased AND
    its magnitude exceeds the traction
    threshold.
Since the rear wheels lost traction
    the friction of the contact patches
        MUST HAVE decreased;
    so, the normal forces MUST HAVE
    decreased.
Consistent with the accelerometers.
```

Figure 3-1: Ex post facto explanation generation process

3.2.1 Data Generation and Analysis

My method relies on collecting data from a plausible vehicle simulation. My collaborators and I developed a basic vehicle simulation using the Unity game engine [75]. The simulated vehicle has physical properties like tire friction and basic vehicle internals, at a level of fidelity sufficient to test my analysis pipeline.

Data Log Generation

The vehicle simulation, in response to user control of a simulated vehicle, produces data traces corresponding to quantities that are tracked by commonly installed vehicle sensors communicating on a typical vehicle CAN bus, like accelerometer data, wheel rotation rates, and driver input state. To generate the necessary data corresponding to an accident scenario, I built a model highway interchange in the simulation, and then drove the simulated vehicle in a variety of accident regimes. A mock up of this highway interchange is in Figure 3-2.

Figure 3-2 shows a car entering an oversteering skid on a freeway off-ramp. A skid occurs when the vehicle tires lose traction on the road surface. An oversteering skid occurs when the rear wheels of the vehicle lose traction but the front wheels do not. An oversteering skid can occur when brakes are applied during an otherwise controlled turn while the vehicle is moving at high velocity resulting in loss of friction

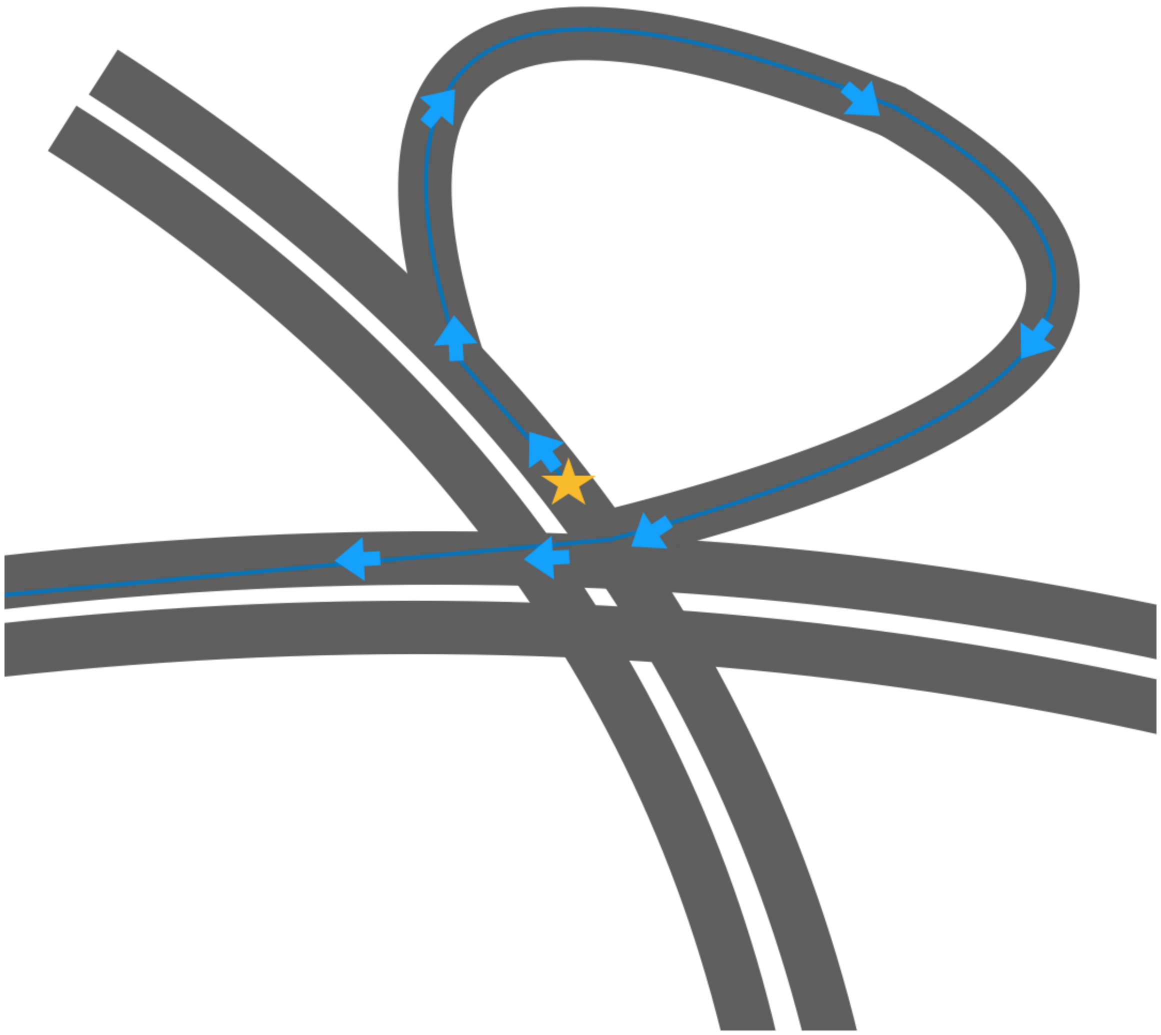


Figure 3-2: A difficult driving scenario inspired by the off-ramp of Route 95 in Massachusetts. The yellow star signifies the starting point, and blue arrows show the vehicle's ideal trajectory.

```
56.105 22 1.34
56.105 23 1.34
56.105 25 1.07
56.105 30 0.00
56.105 B1 9799.55 9848.86
56.105 B3 9848.39 9897.63
56.105 120 13 04 50
56.105 244 0.29
56.105 GroundTruthXYZ 4.37 5.05 45.25
```

Figure 3-3: A sample CAN bus data record. Each line has a time stamp, CAN bus code, and parameter information. The mappings for the CAN bus codes are in Appendix B-1.

on the rear wheels and in lateral motion of the rear of the vehicle. I performed 4 simulation runs to replicate the described event, gathering test traces to use for the developed analysis pipeline.

Data Log Format

The vehicle log data mimics a typical vehicle CAN bus format. There is a time stamp, a CAN bus code (corresponding to a vehicle specific module), and parameter information (which varies in length and format, depending on the CAN bus code). In the simulation, a CAN bus snapshot, with the 9 different CAN bus readings, is produced every .005 seconds[2]. I represent each CAN bus snapshot as a `log-snapshot`. The CAN bus code mappings are in Appendix B-1. A sample of a CAN bus record is in Figure 3-3.

Log and Event Analysis

Each `log-snapshot` is indexed by the corresponding time. I filtered these `log-snapshots` into "intervals of interest" using edge detection and interval analysis. In pre-processing, the data is smoothed with an average pass filter.

Edge detection identifies specific intervals where edge events occurred. The edges are represented as rules: when the brakes were applied, or when the car accelerated.

[2]The simulation environment will generate up to 13 CAN bus codes when it is in "autonomous" mode. The extra information is used for LiDAR interpretation.

```
(define (isBraking? snapshot)
  (eqv? (log-snapshot-brake snapshot) 0))

(define (isAccelerating? snapshot)
  (eqv? (log-snapshot-accel snapshot) 'inc))
```

Listing 1: Braking and accelerating rules for edge detection. Note that braking is indicated by a 0 reading. The `inc` reading indicates that the reading has increased between the the last snapshot and the current snapshot.

X before Y	XXX YYY
X equals Y	XXX YYY
X meets Y	XXXYYY
X overlaps Y	XXX YYY
X during Y	XXX YYYYY
X starts Y	XXX YYYYY
X finishes Y	XXX YYYYY

Table 3.1: The complete set of the possible relationships among time intervals, as determined by James F. Allen [6].

These specific edge examples are in Listing 1, and a comprehensive list of edge rules are in Appendix B-2. I filtered the data to find intervals that adhere to these edge detection rules over successive `log-snapshots`. This results in braking intervals, accelerating intervals, right turning intervals, etc. I filter the edge event intervals that satisfy the temporal relationship description of particular events. For example, once I have braking intervals, I want to find the intervals within that where the vehicle is turning, or where the vehicle came to a complete stop. I represented these events as a combination of intervals using Allen's Interval Algebra [6] shown in Table 3.1 to find intervals that work together to make an "interval of interest." An example is in Table 3.2. I use these intervals of interest as input to the models, which form a story of what happened during a particular time span.

18:10:25.333	GPS: Heading 321.16, Speed 60.3mph
18:10:26.500	Operator: Brake 0.35, Steer 5.0
18:10:26.560	Driver assist: Brake 0.4
18:10:27.867	GPS: Heading 353.84, Speed 52.1 mph
18:10:29.970	Operator: Brake 0.90, Steer 9.3
18:10:30.010	Wheel Rate Monitor: Skid
18:10:30.040	GPS: Heading 28.27, Speed 0.0mph
18:10:30.070	Wheel Rate Monitor: Skid
18:10:30.170	Operator: Brake 0.91, Steer 6.6
18:10:32.933	GPS: Heading 129.08, Speed 0.2mph
18:10:35.140	Operator: Brake 0.93, Steer 0.0
18:10:35.467	GPS: Heading 121.52, Speed 0.0mph
18:10:38.670	Stopped

Table 3.2: Summary of the "intervals of interest" accumulated during an over-steering skid.

3.2.2 Qualitative Algebras

I define a set of qualitative algebras[3] to explain my vehicle scenarios. My first and most used algebra, the qualitative increment, was first defined in de Kleer's PhD thesis [49]. However, in my vehicle models, I also needed qualitative actions: tightening and loosening, and descriptions of vector forces on the vehicles' wheels. Therefore, I developed a set of four qualitative algebras to represent the descriptions of mechanical components and force vectors: qualitative increment, action, direction, and magnitude. The algebras are described in Appendix A.1.

3.2.3 Models

I constructed two models, which combined with generated data, provide human-readable explanations of vehicle behavior. The fully qualitative mechanical model has implicit rules that describe the relationships among the mechanical components of the vehicle. For example, when the tire brake pads are engaged, what other mechanical components are affected? The code for these constraints is shown in Listing 2, which

[3]A qualitative algebra is a description of change with algebraic properties like addition, subtraction, multiplication, etc. It is usually used to represent continuous quantities of the world, such as space, time, and quantity with little "precise" information. For example, representing time with events: event a occurred "before" event b, event b occurred "after" event a, etc. These types of representations can support reasoning, even without precise details.

shows the *causal* properties of tire component of mechanical model. Consider that `pressure` is the pressure of air in the tire. The following are facts:

1. With low air tire pressure (or decreasing pressure), the axle is closer to the road: and the radius of rotation is reduced, causing the rotation rate to increase.

2. This was inspired by the idea that some cars have systems that warn you when your tire pressure is low. This works by measuring the rotation rate of the tires.

3. With under-pressured tires, the speedometer will display a value greater than your actual speed.

And these facts are expressed *qualitatively* in Listing 2, so that tire pressure is the inverse of the qualitative value of the rotation rate. This builds on other "common sense" facts: when the tire brake pads are engaged, the wheel rotation rate is certainly decreasing. However, if the wheel rotation rate is decreasing, that does not necessarily imply that the tire brake pads were engaged. The vehicle could be going uphill, or the vehicle could slowing down due to the force of friction on the tires.

To provide detailed explanations of why a particular event occurred, I developed a semi-quantitative physics-based model which quantitatively calculates forces on the vehicles wheels and combines that information with measured data to provide qualitative explanations. Both models are written in MIT/GNU Scheme and rely on the existing propagator system, described in Section 3.2.4.

3.2.4 Vehicle Modeling with the Propagator System

The Art of the Propagator System is a qualitative reasoning system that maintains dependencies that can be used to construct an explanation of how a command to the effectors or an intermediate value was determined. Part of those dependencies are causal chains that come from the expectations determined by the model, and some will be constraints coming from recorded data. The propagator system [184] can merge measurements with deductive reasoning and track dependencies. Propagators

```
(define (tire-object diameter-input pressure #!optional given-name)
  (physob (list diameter-input)
          (lambda ()
            (let-cells (rotation friction (diameter diameter-input))
                       (copier pressure friction)
                       (inverter pressure rotation)
                       (define (insides-name message)
                         (case message
                           ((diameter) diameter)
                           ((pressure) pressure)
                           ((rotation) rotation)
                           ((friction) friction)
                           (else #f)))
                       insides-name))
          (if (default-object? given-name)
              `(,type ,(map name diameter-input))
              given-name)))
```

Listing 2: Propagator code that shows the causal properties of a tire object. The tire pressure is the inverse of the qualitative value of the rotation rate.

implement a way to build distributed, concurrent computational models interconnected by shared cells. Each propagator continuously examines its neighbor cells adding information to some, based on deductions it can make from the information in others.

Consider, for example, the block diagram of the throttle control system in Figure 3-4. A qualitative model of this system can be made from this diagram. Each wire can be modeled by a propagator cell that holds information about the signals on that line. Each block in the diagram can be modeled by a propagator that constrains information contained in the cells that model the wires incident on it. Although the diagram indicates that information flows in specific directions, propagators can make deductions about inputs from information about outputs as well as in the indicated direction.

In any particular situation the models and the data will converge to some approximate agreement if the models are good enough. There will be many points of agreement where the data will be what is expected and there may be points of dis-

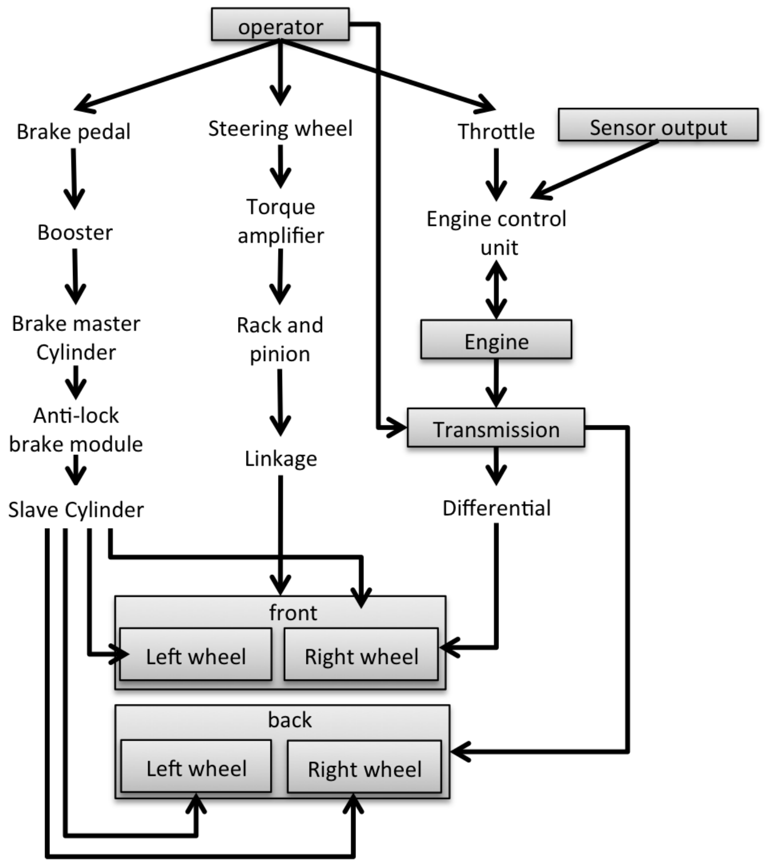


Figure 3-4: A diagram of the mechanical model that describes the interactions between the vehicle's mechanical parts.

agreement. Points of disagreement indicate inadequacies of the models or failures of some part of the real mechanism to do what is expected of it.

3.2.5 Qualitative Mechanical Model

The qualitative mechanical model describes the interactions among the vehicle's mechanical parts. The mechanical components are modeled from the diagrams and descriptions in an automotive handbook [187]. Currently, the mechanical model is relatively simple, only modeling the braking system, steering system, and engine as shown in Figure 3-4. The sensor output is not yet implemented in my system. While my model is a simplification of real-life behavior of a car, its lower complexity enables intuitive explanations, which users can understand. Therefore, the rules of the system

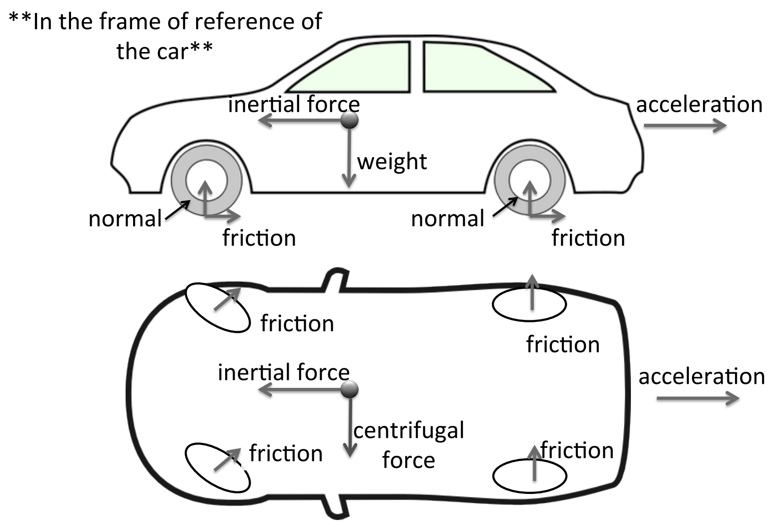


Figure 3-5: The forces that are calculated and used in the semi-quantitative physics model. Shown from the lateral and top-down view.

are intuitive, and the system does not require complex equation.

The mechanical model is initialized with a specific time interval, where each data value (e.g., brake pad pressure change, steering change, etc.) is a qualitative increment, representing the qualitative change during that time span. The model is then run by propagating the data-initialized qualitative values through the system. Specific model values can be queried using `explain-readable` and `inquire-readable`, described further in Section 3.2.7.

3.2.6 Semi-quantitative Physics Model

The physics model calculates forces on the vehicle's wheels, and then constructs causal chains; some coming from expectations determined by the model, and some coming from recorded data. Unlike the mechanical model, which is initialized by recorded data, and then queried for values and explanations, the physics model is initialized by the log data, but also uses that log data values to provide evidence in its deductions. The forces that are calculated and then explained are shown in Figure 3-5. Recall, this model is a simplification, so that I can use rules of naive physics [92], without solving complex equations.

The models are used at the same time. Therefore, the physics model is especially important when the vehicle's actions are unexpected and not interesting from the mechanical model standpoint. For example, if a skid occurs, the mechanical model will only be able to describe the wheel rotation rates in terms of qualitative increments, which does not provide the explanation for a skid. Instead, using the physics model, a skid can be identified by the rear or front wheels losing traction. The wheels lose traction by a decrease in normal force.

3.2.7 Reasoning

My system outputs readable explanations from the dependency tracking elements of the propagator system. Most of these explanations are rule-based: outputting a more readable version of an `explain` command, which is implemented in the propagator system. The propagator has two explanatory functions: `inquire` and `explain`. The `inquire` command displays the immediate values of the inquired cell, and the `explain` command recursively displays every dependency in that cell's inquiry in the system. I implemented two other explanatory functions, `inquire-readable` and `explain-readable`, which display the dependencies tracked through the system in more readable language. For example, the `inquire` and `explain` display the cell's dependent functions and values without explaining them, whereas `inquire-readable` and `explain-readable` explicitly cite the reasons, inputs, outputs, premises, and displays the cell value in readable form.

It is important to note the distinction between deductions and expectations. In my work, I deduce based on a casual chain of expectations. My assumptions are certain; I expect the mechanical devices within the car to act a certain way, and at the same time, I can expect the physics of the vehicle to act a certain way.

3.3 Experiment Results

The experiments displayed in this section, although not all inclusive, highlight the more "interesting" events that my system can detect and explain.

3.3.1 Examples from the Mechanical Model

The mechanical model propagates observed data through the different mechanical subsystems of the vehicle. The model is initialized by the observed data, and then those values are propagated through the system appropriately. Consequently, the user is able to query specific components of the system, and a readable explanation can be displayed through the appropriate command.

I provide two examples below from the same interval in a normal driving scenario where the vehicle is braking. During a braking interval, I expect that the anti-lock brakes are engaged (so that the hydraulic brake pressure is `increasing` and the wheel rotation rates are `decreasing`). In the first call to `inquire-readable`, I check the hydraulics on the antilock-brakes are increasing. The model also finds the premises, or root causes for this change: there is a braking change in that interval (from the method `brake-change-from-initialized-interval`)). In the second call, I examine the same interval and find that the wheel rates (specifically the left-front wheel) is decreasing. Further, the model is able to pinpoint *why* this change happened; by pointing to the specific interval event change: `wheel-change-from-initialized-interval`.

```
>> (inquire-readable
(hydraulic antilock-brakes))
(hydraulic antilock-brakes) has the value
increasing change
  Reason: function (+)
    inputs: front-brakes-pressure
                (booster antilock-brakes)
    outputs: (hydraulic antilock-brakes)
  Premises:
  (brake-change-from-initialized-interval)

>> (inquire-readable left-front-wheel)
left-front-wheel has the value
```

```
decreasing change
  Premises:
  (wheel-change-from-initialized-interval)
```

From the model, I am able to query different internal mechanical devices, like the hydraulics, and I can also query the data directly, like the left-front-wheel rotation rate. Notice that the left-front-wheel has no inputs because it is a data input. The initialization, which I named to be `wheel-change-from-initialized-interval`, is the premise which tells the `left-front-wheel` to be exactly the value decreasing change. While this model is useful for debugging mechanical systems, it requires physics knowledge to be able to model complex vehicle behavior like skids.

3.3.2 Examples from the Physics Model

The physics model propagates the underlying forces on the wheel of an average front-wheel drive sedan. The model is initialized by the acceleration forces (both lateral and longitudinal) and calculates what is the appropriate magnitude of forces on the car's wheels. The first example is of skid behavior. In this scenario, B.Z. Yuan and I simulated an oversteering skid [75], where I expect that the rear wheels of the vehicle lose traction but the front wheels do not.

```
(explain-readable-forces normal-forces)
REASON: rear-wheels-force decreased AND
its magnitude exceeds the traction
    threshold.
    Since the rear wheels lost traction
    the friction of the contact patches
    MUST HAVE decreased;
    so, the normal forces MUST HAVE
    decreased.
  Consistent with the accelerometers.
QUALITATIVE TIRE SUMMARY:
    The left front normal force decreased.
    The right front normal force increased.
    The left back normal force decreased.
    The right back normal force decreased.
```

The above explanation was automatically generated by explaining the normal forces during an oversteering skid interval. The more detailed explanations are generated by aggregating quantities and qualitative reasons that are set after running the physics model.

```
(explain-readable-forces normal-forces)
REASON:  right-wheels-force increased AND
its magnitude is within traction threshold.
     Since the right wheels are gaining
     traction
     the friction of the contact patches
     MUST HAVE increased.
     so the normal forces MUST HAVE
     increased
     So the car is turning left safely.
  Consistent with the steering
  and accelerometers.
QUALITATIVE TIRE SUMMARY:
    The left front normal force decreased.
    The right front normal force increased.
    The left back normal force decreased.
    The right back normal force increased.
```

The above explanation was automatically generated by explaining the normal forces during a left turn.

3.4 Applying this Methodology

The results I presented are for *specific* vehicle models on a *specific* simulated data. In this section I describe the requirements to apply this methodology to a new application. This methodology is designed for *complex* systems (systems with multiple parts) and *time-series* data.

1. Data: A data schema has to be defined, like the `log-snapshot` that I used for the simulated vehicle data. Specific edge-detection rules need to be defined (based on the data schema).

2. Models: The models have to be defined for each system. I have defined a number of vehicle modules which can be re-used. For other applications, the complex systems needs to be decomposed into separate propagators (corresponding to each part), and cells (representing the shared communication between parts).

3. Reasoning: The reasoning process *uses* the data and defined models. The reasoning artifacts: `explain`, `explain-readable`, `inquire`, and `inquire-readable` are applicable to other propagator models.

3.5 Related Work

There have been many contributions in the space of reasoning for qualitative change. The term incremental qualitative (IQ) analysis was coined in Johan de Kleer's PhD thesis [49]. Incremental qualitatives represent quantities by how they change when a system itself is changing. Incremental qualitatives are represented by four values: increasing, decreasing, no change, unknown change. In his thesis, de Kleer describes this qualitative algebra, which I extend in this work to represent different algebraic operations. De Kleer and Forbus also wrote a book on efficient logic truth maintenance systems (LTMSs) [61] to propagate constraints, however, it lacks the verbose explanatory capability necessary for my system's verbose goals.

Using back propagation to reason about complex behavior has also been well studied in the field. Models that can merge measurements with deductive reasoning and that can track dependencies are captured with propagators [184]. This language is a way to build distributed, concurrent computational models, based on the idea that computational elements, called propagators, are autonomous machines interconnected by shared cells. Each propagator continuously examines its neighbor cells adding information to some, based on deductions it can make from the information in others. These models are implemented in MIT/GNU scheme with the propagator framework.

In vehicle specific modeling, Stuss and Fracci presented a qualitative model of a vehicle braking system [214]. Their major contribution is a model-based automation of failure-modes-and-effects analysis (FMEA), with the specific application to a vehicle braking system. While their results do not include explanations, their model motivated my own research. They are able to infer braking component behavior from the models' inputs, similar to the way that my models can infer changes. This chapter is a more comprehensive application of the same process. As far as I know, this is the first application of qualitative reasoning to provide explanations of complex and comprehensive vehicle actions.

3.6 Limitations

One limitation of the system is that the physics and mechanical models are separate. With a combined model, and more detailed sensor data, I could model more complex physics over complex terrain. For example, for a turning radius and a friction coefficient for what speed will the car skid? And if we observe that the car is decelerating, is this caused by the brakes, or by the hill or both? I developed a naive query language to find edge cases, but a more sophisticated language is required for different parts. Another limitation is that the CAN bus data is simulated. Simulated data cannot represent all possible failures. Applying this methodology on a real vehicle may be explored in future work.

The explanations presented in this chapter are static. To be used in a running vehicle, my models would need to provide *dynamic* explanations. This would require some optimization in order to be used in real time. But the qualitative deductions from the running logs might be used to improve the control strategies in vehicles with significant autonomy. I explore the use of explanations to improve decision making in Chapter 6.

3.7 Contributions

In modeling a system of a modern vehicle, I have really created a model of the “mind” of a car. This is similar to the methodology in the Society of Mind [158]; a “modern” vehicle is a system made up of lots of pieces that individually handle different tasks, like anti-lock braking, power steering, and obstacle detection. Similarly, the human mind can be thought of as a set of various pieces that do different jobs and speak very different internal languages. My goal is to construct a model of a car mind made of up different parts that can “share stories” with each other. I explore this idea in our work so far in a limited setting with cells in a propagator-based system, where the “sharing” of information is done via the propagator rules. I take this a step further by applying these ideas to full-sized systems, in which the communicating parts are entire electromechanical modules, and the stories shared with each other collectively contain enough detail to permit reconstruction of adequate explanations of particular phenomena.

But what happens when we cannot create models? Some of the best problem solvers, like AlphaGo and Deep Blue, are impossible to model: they are opaque. They cannot explain their actions, or justify their reasoning. In the next chapter, I propose a solution for opaque subsystems, “reasonableness monitors,” an explanatory sanity check that justifies decisions with commonsense knowledge and rules. This builds on the key idea of this chapter: every agent is constantly developing a plausible story about its neighbors.

Chapter 4

Reasonableness Monitors

"We can often enhance our ability to deal with a complex problem by adopting a new language that enables us to describe (and hence to think about) the problem in a different way, using primitives, means of combination, and means of abstraction that are particularly well suited to the problem at hand."

– The Structure and Interpretation of Computer Programs [3]

One component of a complex machine, such as a self-driving vehicle, can be an opaque subsystem. Most of these opaque subsystems are machine learning models that are tailored for a particular problem. When applied to unexpected scenarios in critical domains, these models make fatal mistakes [11].

I present a sanity check for opaque subsystems: a monitoring framework that can judge and justify whether the underlying opaque decision or action is reasonable or not. This monitoring framework, called *reasonableness monitors*, can be customized for different domains, since it utilizes a standard vocabulary and rule language. The input to the monitoring system is the output from an opaque learning system: an intended behavior, which is parsed into a common representation. The monitor uses a reasoner to find the important concepts leading to contradictions between expected behavior and anomalous behavior, which is tracked back to a constraint or rule.

The output of a reasonableness monitor is a human-readable explanation succinctly describing the core reasons and support for an intended behavior. The goal of reasonableness monitors is to improve the performance of individual (i.e. local) opaque subsystems, by performing a "last-pass" check for clearly unreasonable outputs. In this chapter, I contribute two implementations of *reasonableness monitors.*

1. An end-to-end prototype for machine perception [79, 74] in Section 4.2.
2. A generalized framework [78] in Section 4.3.

4.1 Introduction

When opaque subsystems make mistakes, we would like to know why the error occurred. But diagnostic systems [53] require access and knowledge about the underlying mechanism, which may be implausible [149]: the underlying subsystem may be uninterpretable (black-box), or inaccessible (proprietary or trade-secret). Therefore, I *monitor* a subsystem's output, assuming limited knowledge of underlying processing or method.

How does this monitor ensure that the underlying subsystem is acting reasonably? The monitor needs a lot of world knowledge. But that knowledge also needs to be *structured*, so that the monitor can find the *important concepts* leading to unreasonable behavior. The monitor is able to *judge* whether a behavior is reasonable or not by tracking the behavior back to a constraint or rule. This relies on a rule language for constraints/policies, ontologies for representing data/knowledge, and a reasoner all leading to an explanation of reasonableness.

The ability to provide coherent explanations of complex behavior is important in the design and debugging of such systems, and it is essential for societal confidence in technology: explanations support reasoning, leading to the belief of competence and integrity of algorithms.

4.2 Method Overview

I describe an end-to-end reasonableness monitor for machine perception. A machine perception system, or an image captioning system, produces perception descriptions.

In this section, I refer to the input to a reasonableness monitor as a *description*.

4.2.1 Input Parsing

The input of the reasonableness monitor is a perceived scene *description* that contains a subject (or actor) and a verb, at minimum. I used the Python NLTK part-of-speech (POS) tagger [24] to tag each word of the description. I wrote a regular expression parser which maps the POS tags to specific noun, verb and object phrases. The parsing code is in Listing 3.

```
def parse_with_regex(words):
    tags = nltk.pos_tag(words)

    parser = nltk.RegexpParser('''
    NP: {<DT|PRP$>? <JJ>* <NN|NNP|PRP>*} # NP
    P: {<IN|TO>}           # Preposition
    V: {<V.*>}          # Verb
    PP: {<P> <NP>}      # PP -> P NP
    Adv: {<RB|RBR|RBS>} # Adverbs
    VP: {<V V*> <NP|PP>*}  # VP -> V (NP|PP)*
    ''')
    result = parser.parse(tags)
    result.draw()
    return result
```

Listing 3: Regex parser for the end-to-end reasonableness monitoring system. The `result.draw()` command will display the parse tree. A sample parse tree is in Appendix B-4.

4.2.2 Representation: Conceptual Primitives

The parsed description is processed into abstract role frames. In the end-to-end representation, I used Roger Schank's Conceptual Dependency (CD) [198]. I chose Schank's representation because it represents physical acts in a universal, language-free conceptual base. The CD primitives are also small in number, and only six "physical" primitives[1] were needed in my prototype system[2]. The conceptual primitives are described in detail in Appendix A.2.

Building Conceptual Primitive Frames

My system needs to determine which CD primitive to use. It does this by searching for paths between the verb and an *anchor point* in ConceptNet. An *anchor point* is a concept that fulfills a broad categorization for a CD primitive act. Table 4.1 lists the anchor points used for selecting the conceptual primitive acts. I specifically chose anchor points to best represent the conceptual primitive. For example, the conceptual primitive "GRASP" is not commonly used in natural language. "Grab" is a more popular verb that is synonymous with "GRASP," so "grab" is set as the anchor point for the GRASP primitive act.

Multiple anchor points are used for some primitives. For the MOVE primitive, "move" and "action" are used as verb-to-primitive anchors. The specific name of the conceptual primitive is not always used, and sometimes I chose certain words as anchor points because they were better represented in ConceptNet. For example, the verb "ingest" has very few edges in the ConceptNet network, so instead I chose "eat", "drink", and other words with similar meanings for the INGEST anchor points. A table of the anchor points for each CD primitive can be found in Table 4.1.

Anchor Points for Primitive Acts

My system queries ConceptNet using the stemmed and lemmatized form of the verb, searching for paths from the verb to the anchor point representatives of the CD primitives. The verb is anchored to the closest anchor point in terms of `IsA` hops in ConceptNet's semantic network. My system instantiates a CD transframe of the corresponding primitive to represent the input description.

[1]The six physical primitives account for *most* actions: INGEST, EXPEL, GRASP, MOVE, PROPEL, and PTRANS. I focused on the physical action primitives because actions are present in image descriptions, whereas mental state primitives like MTRANS and MBUILD are not.

[2]Conceptual primitive frames are synonymous with transframes [157].

Table 4.1: The Conceptual Dependency (CD) "physical" primitives used, and the ConceptNet anchor points used to bind them to incoming verbs.

CD Primitive	Anchor Point(s)
INGEST	eat, drink, ingest
EXPEL	expel
GRASP	grasp, grab
MOVE-PTRANS	move, action, go
PROPEL	propel, hit

Anchor Points for Primitive Roles

A different set of anchor points is used on the concepts filling the actor, object and direction roles of the frame to determine if they satisfy or violate the frame's constraints. I set constraints for the subject and the object, using the definitions of each CD primitive frame.

The reasonableness monitor uses six anchor points for these roles: person, plant, animal, object, vehicle, and weather. These anchor points were chosen for two reasons. The first reason is that they fit the use case of autonomous vehicles. The second, more significant reason is that each anchor point is broad enough to include a variety of items, but just restrictive enough so that each anchor point has different properties that allow it to perform certain actions.

For example, an animal can move on its own, and thus it can serve as the actor role in a MOVE-PTRANS CD transframe, but an object cannot move on its own, unless it is a vehicle. I assume that vehicles are controlled by humans and therefore they can move, so I also have an anchor point so that cars or other automobiles will not be categorized as objects, but as vehicles specifically.

Primitive Act Constraints

All physical primitive acts are subject to constraints that can be applied to the actor, object, and direction cases of the frame to determine reasonableness. For all of these primitives:

Table 4.2: List of ConceptNet anchor points used for actor and object roles in the CD transframe, and constraints on where a concept may reasonably serve in the role.

Anchor Point	**Actor Constraints**	**Object Constraints**
person	EXPEL, GRASP, INGEST, MOVE, PROPEL	GRASP, MOVE, PROPEL
animal	EXPEL, GRASP, INGEST, MOVE, PROPEL	GRASP, INGEST, MOVE, PROPEL
plant	none	GRASP, INGEST, MOVE, PROPEL
object	GRASP	GRASP, INGEST, MOVE, PROPEL
place	none	none
weather	PROPEL	none
confusion	PROPEL	none
vehicle	EXPEL, GRASP, INGEST, MOVE, PROPEL	MOVE, PROPEL

- The actor must be an "animate" object or thing capable of
    1. making other objects move (in the case of MOVE, INGEST, EXPEL).
    2. moving or applying a force in order to GRASP another object (in the case of GRASP).
    3. applying forces to other objects (in the case of PROPEL).
- The object must be a physical object, thing, substance, or person.
- The direction case should represent a direction in reference to a physical object or a physical location or place.

There are several additional constraints for particular primitive frames and the complete constraints for actor and object cases of the CD primitives are shown in Table 4.2. Based on its definition, each primitive imposes constraints on the types of anchor points that the subject and object can be categorized as. In order for the statement to be reasonable, both the subject and the object must share an edge with one of their respective permitted anchor points. If either of them do not share any edge with the permitted anchor points, there is a contradiction and the statement is deemed unreasonable.

For example, in the description: "a mailbox crosses the street", "mailbox" violates the constraint that the actor in the MOVE primitive be animate. Taking another example, for the statement “A man pushes the wind,” my system creates a PROPEL primitive, and “man” will be categorized as a person anchor point, which fits the subject constraint. However, no edge exists between any of the permitted anchor points and the object, “wind”, because wind is not a thing (a person, animal, vehicle, or object). Therefore the statement will be deemed unreasonable.

Compound Primitive Frames

A reasonableness monitor can also construct a Conceptual Dependency transform using multiple primitives. For example, in the description “Lisa kicked the ball,” there are two primitive acts. Firstly, Lisa applies a force (PROPEL), and secondly, the ball is moved (MOVE-PTRANS). Although my system cannot automatically decompose this sentence into compound primitive frames, I hard-coded select verbs to be compound by default (instead of using ConceptNet or anchor points), so that kick decomposes into a PROPEL and MOVE-PTRANS. The resulting justification does not change, but the explanation is more verbose [79].

Establishing Context

It is possible for the context of a sentence to change its reasonability. For example, weather may change the reasonability of a statement, as it can easily change the CD primitive chosen. To illustrate, I refer to the example: “a mailbox crossed the street.” This is deemed unreasonable since “cross” is a MOVE-PTRANS type and a mailbox is an object, which conflicts with the actor constraints of MOVE-PTRANS. If instead the description were “a mailbox crossed the street in a hurricane,” then the description becomes more reasonable. An outside force, such as a hurricane, can move objects, which corresponds to the definition of PROPEL. Therefore, the CD primitive frame becomes a PROPEL rather than MOVE-PTRANS. Since the mailbox satisfies the constraints for PROPEL, this statement is now classified as reasonable.

My system also checks for prepositional phrases as added context for establishing reasonableness. When the sentence is parsed, prepositional phrases are identified and stored as contexts which are additional evidence in the CD primitive structure. In a case like “in a hurricane,” the noun phrase within the prepositional phrase is bound to another anchor point, in this case “hurricane”. There are also anchor points for extreme conditions that are hard coded, where ConceptNet is not used, i.e., hurricanes, earthquakes, tornadoes, and floods. In the reasonableness checking phase, the monitor also examines this context to determine if the additional context can ameliorate a previously unreasonable description.

4.3 Adaptable Implementation

In this section, I describe an adaptable implementation of reasonableness monitors. I show results on two use cases: descriptions of perception (which could be generated from a machine learning scene understanding systems), and vehicle plans (from an autonomous vehicle planning system, which could be proprietary). I describe how to apply this framework to other domains in Section 4.5. A schematic of the reasonableness monitor as an adaptable framework is in Figure 4-1.

4.3.1 Log Generation and Ontology

In the adaptable implementation, I require that the log, or data, is constructed in RDF, which is a World Wide Web Consortium (W3C) standard[3]. RDF allows for data descriptions and relationships between data in terms of triples[4]. The RDF log contains the system state in terms of symbolic triple relations. An example RDF log is in Listing4. It contains the subject, predicate and object of the input description, and relevant descriptions aggregated from the commonsense database. This aggregation utilizes RDFS (the RDF Schema), a semantic extension of RDF, allowing for additional mechanisms for describing groups of related resources and the relationships between these resources.

For perception, I generate the RDF log for a description by parsing for relevant concepts. From the input of a natural language description, I use a regex parser in

[3]RDF Documentation: `https://www.w3.org/TR/rdf-schema/`

[4]Triples suffice for the reasoning in this chapter. Note that a problem with RDF is that you cannot have information that refers to another triple. In Chapter 7, I use triples with added *indexes*

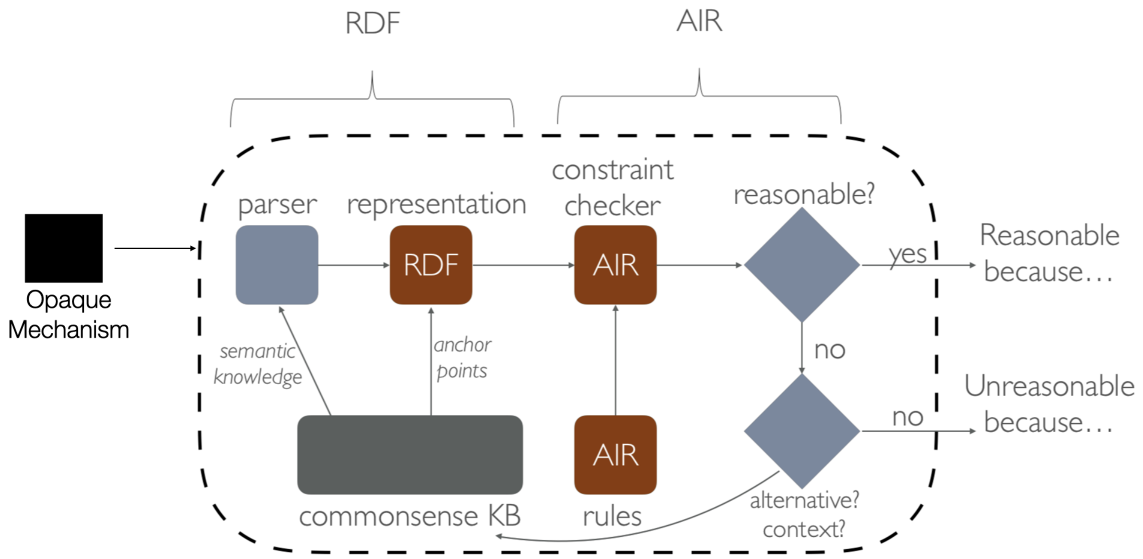


Figure 4-1: The system diagram schematic of a reasonableness monitor as an adaptable framework.

Python to extract the noun phrase, verb phrase, context information (prepositional phrases) to identify the actor, object, and action of the description. The development of an ontology is incorporated with the process of developing the log data. For this perception description use case, I develop a set of anchor points to extract commonsense knowledge from ConceptNet, and primitive actions represented as a conceptual dependency primitives. This conceptual dependency primitive will be used to construct rules, with the actor, object, and context information as input. An example of a parsed description represented as an RDF log is in Listing 4. An example of an RDF log for a vehicle sample is in Listing 19 in Appendix B.5.2.

For vehicle planning, the process is extended with the same parsing process, the representation is extended to include vehicle primitive actions like yield, move (with speed and direction), stop and turn. Context is also extended to cover external factors that are specific to vehicle planning like stop lights, pedestrians, and weather.

```
foo:my_actor
    a ont1:Subject ;
    ont1:phrase "a wall" .

foo:my_object
    a ont1:Object ;
    ont1:phrase "the street" .

cd:move
    a ont1:Move ;
    ont1:actor foo:my_actor ;
    ont1:object foo:my_object ;
    ont1:verb "cross" .
```

Listing 4: The RDF log of "a wall crossing the street."

4.3.2 Rule Input

It is required that the rules are written in AIR (AMORD In RDF)[5]. AIR is a Semantic Web-based rule language that can generate and track explanations for its inferences and actions and conforms to Linked Data principles. Another advantage of AIR is that it supports Linked Rules, which can be combined and reused in a manner similar to Linked Data. Since the AIR explanations themselves are Semantic Web data, they can be used for further reasoning. A benefit to using these Semantic web standards and data is that you can find related data, rules and concepts easily.

For the perception problem, the rules are from Schank's conceptual primitives [198]. An example rule for the primitive "MOVE" is that the actor must be animate, or the actor must be propelled by something. Other rules require more commonsense knowledge—for "INGEST" the action of consuming food and drink must be through the mouth or stomach of the actor.

For the vehicle planning problem, rules are derived from the Massachusetts driving handbook. These rules can be changed to express the rules of the road for other states and areas. For example, the "right on red" turning rule is explicitly banned in most intersections in the greater Boston area, although legal in the state of Massachusetts. A subset of basic driving rules are shown in the Appendix in Listing 14. One example

[5]AIR is freely available: `http://dig.csail.mit.edu/2009/AIR/`

```
:pedestrian-rule a air:Belif-rule;
     rdfs:comment "Ensure that pedestrians are safe.";
     air:if {
            :EVENT a :V;
                   car_ont:InPathOf :V.
    };
    air:then [
             air:description ("There is a pedestrian");
             air:assert [air:statement{:Event
                         air:compliant-with :safe_car_policy .}]] .
    air:else [
             air:description ("There is not a pedestrian");
             air:assert [air:statement{:Event
                         air:non-compliant-with :safe_car_policy .}]] .
```

Listing 5: The "pedestrian right-of-way" rule in AIR.

is the "pedestrian right-of-way" rule in Listing 5.

Rules were constructed automatically and manually validated. In the automatic part, I wrote a script to read in and process the Massachusetts driving handbook[6]. From the natural text, sentences were flagged as "probable" rules if they contained "rule" keywords: if, then, else, because. Air rules were constructed from natural text using a parser. The automatic rule extraction is covered in more detail in Chapter 6. In the automatic process, my script generated 221 rules, which I filtered down to 90 rules[7].

4.3.3 Reasoning and Explanations

AIR captures the reasons and descriptions necessary to output explanations. Using Python and RDFLIB[8], the output RDF file is parsed for the justifications and rule descriptions, which are combined together into a human-readable explanation. For example, if the pedestrian rule is violated, then the resulting description is "pedestrian

[6]The Driver's manual was accessed here: `https://driving-tests.org/wp-content/uploads/2020/03/MA_Drivers_Manual.pdf`

[7]I may examine how to automatically combine and filter rules in future work. The goal of this chapter is *using* rules, and not necessary *creating* rules. Creating rules is discussed in Chapter 6. The implementation is in the Appendix in Listing 20.

[8]`https://github.com/RDFLib/rdflib`

detected." This is combined with the other rules fired (e.g., the speed rule—do not make a sudden stop at high speeds) to create the explanation— "Since there is a pedestrian in the road, move is unreasonable."

4.4 Evaluation

The monitoring system is evaluated in two ways: by validating the judgment of reasonableness, and a user study to evaluate how well the system can generate explanations. The output of the monitor is binary judgment, indicating whether the proposed input is reasonable or not, and a human readable explanation explaining that judgment. Examples of these explanations can be found the appendix. With this evaluation, this work aims to answer the following two questions:

1. How accurate is the system at detecting unreasonability?
2. Are users convinced that the statements provide a convincing explanation for reasonable or unreasonable input?

4.4.1 Validation

Since I have not been able to implement the model on a deployed system with real data, I developed my own test sets based on uses cases from interviews with potential customers. The perception description test set is 100 descriptions that I developed to validate the end-to-end reasonableness monitor in Section 4.2. The descriptions are equally split between unreasonable and reasonable, with different verbs, subjects, objects, and contexts.

For the vehicle action test cases, I developed 24 examples. These examples were generated from four lights (red, yellow, green, no light), three motions (move forward, turn, stop), and a binary choice for obstructions (pedestrian or no pedestrian). For validation purposes, I checked that the monitor can determine whether a perception description or a vehicle action is reasonable or not. Each description of a vehicle action or perception description is labeled with a 1 or 0 as reasonable (1) or unreasonable (0).

The adaptable monitoring system judges reasonableness with 100% accuracy on the vehicle action test set. Since there are a countable number of rules and combinations, this makes sense. If the system is deployed in a working vehicle simulation or platform, more sophisticated and complex rules may be needed. This is discussed in Section 4.6.

4.4.2 User Study

I recruited 100 users from Amazon Mechanical Turk to evaluate the explanations. The study participants were instructed to rate each explanation on a five point Likert scale from "not convincing" to "very convincing."

Participants were presented with 40 explanations, evenly split between reasonable and unreasonable judgments. There were 20 vehicle planning explanations, and 20 perception description examples. I presented only 40 explanations to avoid exhaustion. Participants were instructed to rate how convincing the explanations were, on a scale from 1 to 5. The average score over all explanations was 3.94, indicating that most users were moderately convinced that the explanations. The survey also included an optional question for users to explain why they choose their indicated rating for each explanation. A table of a sample of explanations for the four types of explanations tested: reasonable vehicle plans, unreasonable vehicle plans, reasonable perception descriptions, and unreasonable perception descriptions is in Table 4.3.

Users were convinced of the monitor's explanations, since all explanations were rated at an average above 3.5. A distribution of ratings can be found in Figure 4-2. In general, users were slightly more convinced by two factors. Firstly, reasonable were rated higher than unreasonable statements. This could be due to positive bias [105], demonstrating that people are generally more favorable to positive examples. Secondly, perception description explanations (both reasonable and unreasonable) were rated higher than vehicle planning explanations. This could be attributed to users being less familiar with vehicle rules. Both differences were not statistically signifi-

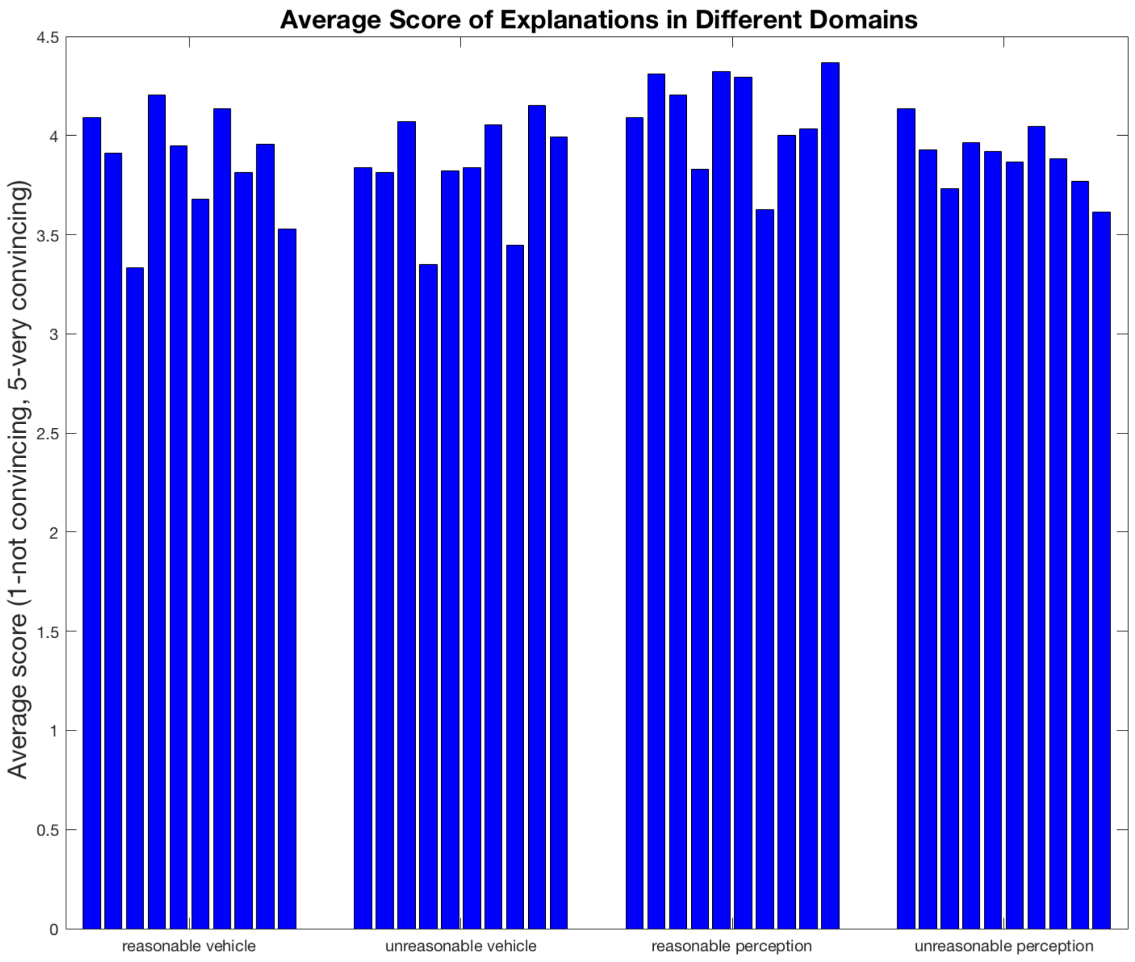


Figure 4-2: Average rating of 40 explanations over 100 user trials. There are 4 sets of explanations (from left to right): reasonable vehicle plans, unreasonable vehicle plans, reasonable perception descriptions, and unreasonable perception descriptions

	Reasonable	**Unreasonable**
Vehicle Plans	Although green means go, green also means yields to pedestrian in the road. Since there is a pedestrian in the road, waiting is reasonable. So it is reasonable for the vehicle to wait.	A yellow light means 'stop if safe', which is inconsistent with go. So it is unreasonable for the vehicle to go.
Perception Descriptions	Although a tree cannot propel something on its own, a storm can propel a stationary object to move. So it is reasonable for a tree to hit a car in a storm.	A laptop is an object that cannot move on its own. So it is unreasonable for a laptop to move without context.

Table 4.3: Comparison of explanation descriptions for the four types of explanations tested: reasonable vehicle plans, unreasonable vehicle plans, reasonable perception descriptions, and unreasonable perception descriptions.

cant.

4.4.3 Example Explanations

The reasonableness monitor fails on some examples. The majority of these failures are due to ConceptNet: the relations are not well-defined. A breakdown of failure cases (and their root causes) is shown in Table 4.4. Table 4.3 displays a few stable explanations. One interesting example of a reasonableness monitor failure is below:

```
Input: A hamburger crossing the street.


This perception is REASONABLE:
A hamburger is an animal that can move on its own.  So it is
reasonable for a hamburger to cross the street.
```

This case is interesting because the monitor judgement is wrong, although the reasoning is sound. The problem is that there is a chain of `IsA` relationships in the commonsense knowledge base that attached hamburger to an animal: `(hamburger IsA food) AND (food IsA animal)`.

		Classify as: Reasonable	Classify as: Unreasonable
Label as:	Reasonable		Parser: 2 ConceptNet: 8
	Unreasonable	Parser: 2 ConceptNet: 6	

Table 4.4: A analysis of the causes of the 18 misclassifications on the 100 test cases.

4.5 Applying Reasonableness Monitors

The adaptable implementation (Section 4.3) can be applied to new applications and domains. The monitoring framework is designed for opaque subsystems where output can be logged[9]. These are the requirements to apply reasonableness monitors to a new application.

1. Data schema: A data schema for model outputs (e.g. labels) and context (e.g. input or meta data) needs to be defined. Commonsense data (or reasonable data) for the *domain* also needs to be given or defined[10].

2. Reasonableness rules: Commonsense rules for the *domain* need to be provided in AIR.

4.6 Limitations

I define reasonableness as a binary value: it satisfies a set of commonsense rules. In the case of vehicle planning, these are the rules of the road. For the perception example, these are commonsense rules for the actor and object of the input description. In reality, reasonableness should be a *score*. Reasonableness scoring is being explored in ongoing work with vector representations of words from GloVe [178], which can calculate the distances between words or concepts.

[9]It is preferable if the output is not time dependent. Otherwise, the methodologies in Chapter 3 can be used.

[10]The commonsense data can also be queried; the search code for ConceptNet in the Appendix B.2.2

This system has *has not* been validated on machine-generated image captions, such as Microsoft's Common Objects in Context (COCO) database [140]. One challenge is that these captions are not necessary unreasonable in the sense that our monitor expects: they are often reasonable because they describe reasonable visual scenes, but incorrect because the description is not correlated with the input image. Another concern is that ConceptNet nodes are identified by words and phrases in "outer" natural language, while CD primitives are meant to be inner-language conceptual representations.

Although this system works fairly well in practice, it does have some obstacles to overcome to become a deployable system. I developed a parser to represent the data in RDF, but this may have to be done manually in different applications, as it may not generalize. The use case of a perceptual "scene understander," sometimes referred to as an opaque, deep neural network, is over-simplified for demonstration purposes. In future work, I may want to apply this system to an actual image captioning system, although their description of "reasonableness" is slightly different. In that context, reasonableness is a caption that accurately describes the intended photo. That kind of monitoring is much harder to enforce than the reasonableness rules that I have defined in this Chapter.

The use cases are simplified for demonstration purposes. The vehicle actions have limited context and perceptual use case is simplified. For a deployed system, these cases will be expanded to cover complex corner cases that are typically not well-represented in the training data.

4.7 Ongoing Work

In ongoing work, I am combining reasonableness monitoring with the causal reasoning models from Chapter 3. Imagine monitors that could not only justify their behavior with commonsense, but also justify their behavior with a causal story. This will require organizational knowledge about the underlying subsystem[11]. I will also use explanatory methods [19, 112] that examine internal representations of an opaque subsystems. Then, I will create a model of the casual links among those representations. Finally, I will incorporate that model into a reasonableness monitor, to explain (1) the internal representations supporting the input subsystem's decision (or not) and to (2) build a symbolic story supporting the subsystem's decision with commonsense and causal reasoning.

4.8 Related Work

One goal of reasonableness monitors is to create safe, trustworthy autonomous systems made out of subsystems that themselves are made out of parts: a "multi-agent system" [158]. Marvin Minsky used the term "agent" to describe any component, subsystem, or part of a cognitive process that is simple enough to understand [210]. Since no single method of problem solving will always work, Minsky suggested that we also need to know about pitfalls and corner cases. He encouraged the use of negative expertise in the form of censor and suppressor agents [159]. Minsky explains that negative knowledge and examples are important to create intelligent systems. He suggested implementing negative knowledge by dividing a complex system into parts that can monitor each other, similar to my monitoring framework.

This chapter imposes sanity checks by monitoring subsystems for reasonable outputs. Monitoring for reasonability is an open topic in computer science. Although formal approaches are provably correct, they do not lend themselves well to an implementation. Collins formal approach based in logic [42] lacks a structural implementation. Cohen's logical theory of reasonable actions [41] represents "language as action," but it is specific to the defined set of reasonable action expressions from logic. While methodological approaches are more generalized, they remain specific to the machine specifications [2] or software specs.

[11]Recall from Chapter 3 that the propagator models need structure. They are, after all, model-based reasoning systems.

Reasonableness monitors represent the input description in terms of conceptual primitives. Roger Schank introduced Conceptual Dependency theory and its conceptual primitives for natural language understanding [198]. Similar work in computational semantics [101], shows that it is necessary to represent these kinds of conceptual structures or thoughts and not simply study language in isolation. There are other choices for compositional decompositions representations [234, 233], including primitives that describe transition space change [26]. Since my domain is a self-driving car, primitives of physical change, like Schank's Conceptual Dependency theory are most applicable.

Reasonable knowledge is provided to the monitoring system from a commonsense knowledge base. In the adaptable monitoring system, this knowledge is parsed into a web standard. Commonsense knowledge bases are key tools for developing systems that understand natural language descriptions and produce explanations. Although CYC is regarded as the world's longest-lived artificial intelligence project [135], with a comprehensive ontology and knowledge base with basic concepts and "commonsense rules," there have been significant challenges to using CYC for NLP [148]. Speer and Havasi [212] demonstrate the usage of ConceptNet5, a freely-available semantic network of commonsense knowledge. Research on SenticNet [32] was inspired by primitive decomposition theories [198], and links ConceptNet concepts to conceptual primitives that help generalize them to overcome linguistic variation. Combining knowledge bases and web standards has been implemented as ConceptRDF; a conversion of ConceptNet to RDF/XML format [166], although the rules are not applied to working system. ConceptNet and rules have been combined for emotion recognition [205], but this work is a combination of rules and common sense for detecting and explaining reasonableness.

Reasonableness is validated and checked with an existing reasoning system. A production quality reasoners keep track of consistencies. Since the adaptable monitor is focused on making a generic monitor using semantic web technologies with RDF (explained below) to represent logs and AMORD In RDF (AIR) [111] as a rule language that supports AMORD-like constructs [116]. AMORD is a rule-based problem solver that keeps track of dependencies, similar to truth maintenance systems [50]. AIR describes properties that can be used to define policies and a reasoner to provide reasons and explanations. RDF[12] is an acronym for the Resource Description Framework, which is a World Wide Web Consortium (W3C) standard. W3C is the main international standards organization for the World Wide Web. While RDF is used mainly for managing and representing data in web frameworks and resources, it is also used in a variety of knowledge engineering tasks due to its triple-store format. This format is useful for representing language (as subject-predicate-object) and for representing premises.

Reasonableness monitors are a system-methodology to identify and explain anomalies in perception, using commonsense knowledge to determine the reasonableness of perception-derived scene descriptions [74, 79]. This work was extended to validate scene descriptions from an immersive virtual reality environment [82]. By contrast, in this chapter, I concentrate on the methodologies, rather than potential applications.

4.9 Contributions

In general, opaque machines and complex algorithms work well in practice. In this chapter, I presented *reasonableness monitors*: a final "sanity-check" for autonomous machines and algorithms, especially those making mission-critical or safety-critical tasks. In Section 4.2, I used conceptual primitive decomposition as the core representation for a monitoring system. I showed how this systems provides succinct, convincing explanations of unreasonable (or reasonable) perceived scenes. In Section 4.3, I extended the CD representation to an adaptable framework, so that reasonableness monitors can be utilized to impose reasonableness sanity checks on various subsystems' outputs.

The key idea here is that monitoring should not be invasive; it should provide an additional set of quick "checks" to ensure more reliability and safety. Automobiles and their autonomous counterparts are engineering marvels, and they work quite well

[12] `https://www.w3.org/RDF/`

most of the time. The idea of reasonableness monitoring is to make them work better by removing blatantly unreasonable situations that can have bad consequences. But monitoring can also be used to alert for help and for developing better benchmarks for safety-critical decisions.

As we add more parts and computational power to these vehicles we not only increase the number of ways for the machine to fail, but also the number of ways the system can be infiltrated. Consider the recent increase in vehicle hijacks [154]. Although monitors may not directly minimize the security vulnerabilities, they will allow infiltrations to be detected in a novel way. Self-monitoring constructs, like the one proposed in this chapter, are a small step towards developing machines without errors, that are more trustworthy, and that perform reasonably, as we expect them to.

Chapter 5

Interpreting Sensor Data

"You could claim that moving from pixelated perception, where the robot looks at sensor data, to understanding and predicting the environment is a Holy Grail of artificial intelligence."

– Sebastian Thrun

A complex mechanism, like a self-driving car, is made out of subsystems that are made out of parts. In Chapter 4, I discussed how to monitor opaque subsystems, e.g, deep neural networks or a proprietary planning algorithm, with commonsense knowledge and rules. But there are other components of a complex mechanism; in fact, almost all complex machines have sensors at various levels of detail. Unlike the opaque subsystems, these sensors output large amounts of data. However, the trouble is *understanding* that data, particularly, in a way that can be understood at a higher, symbolic level, requires an interpreter: a program or method that can analyze sensor data and translate it into a symbolic description.

In this chapter, I present a qualitative sensor *interpreter*. This sensor interpreter builds upon the event-based detection and qualitative reasoning from Chapter 3. It processes a short (10-20 second) sensor interval and outputs a description of what it perceives; particularly the size and movement of objects. A series of test parallel parking simulations show the accuracy and performance of the interpreter on sensory Light Detection and Ranging (LiDAR) data.

There are two phases of this chapter. The first is a proof-of-concept sensor interpreter for simulated LiDAR data. The proof-of-concept is demonstrated on parallel parking examples. The second phase is how to extend the sensor interpreter to current-day LiDAR traces, which have increased in scale and complexity. In Section 5.6, I discuss this problem in detail, and in Section 5.7, I suggest future research directions to incorporate these types of symbolic sensor interpreters into existing point cloud classification methods.

5.1 Introduction

All complex mechanisms have sensors. As a broad definition, "a sensor is a device, module, machine, or subsystem whose purpose is to detect events or changes in its environment and send the information to other electronics, frequently a computer processor. A sensor is always used with other electronics."[1] Sensors are rarely used in isolation. They are necessary inputs to sophisticated subsystems e.g., the anti-lock braking system (ABS), in which the tire sensor consistently monitors wheel rotation rates and recognizes when a sudden change occurs. For example, if the tire sensor detects that the wheels are locking up, the anti-lock braking system attempts to prevent a skid by repeatedly applying and releasing the brakes, automatically [152]. These automatic safety measure can save lives [60].

Outside of the vehicle domain, people interact with sensors everyday. There are sensors in touch-sensitive electronics, e.g., smart phones[2, 3] or even the keys on a keyboard. Sensors are important for my thesis work because they perceive small changes. A humidity sensor can signify changes in weather. A LiDAR sensor uses laser light and reflections to measure distances from neighboring objects.

[1]Wikipedia provides a comprehensive definition of a "sensor" in different applications: `https://en.wikipedia.org/wiki/Sensor`.

[2]One example of a smart phone sensor is the accelerometer which indicates how to rotate your screen: `https://www.nytimes.com/2018/08/07/technology/personaltech/screen-rotate-isnt-working.html`.

[3]Other sensors have implications to personal privacy: `https://www.nytimes.com/interactive/2019/12/19/opinion/location-tracking-cell-phone.html`, but that is out of the scope of this thesis.

5.1.1 LiDAR Sensor Limitations

LiDAR systems have changed the landscape of self-driving vehicle, but LiDAR is expensive to process in real-time. LiDAR can make high resolution maps [33], which has a new purpose applied to detecting obstacles in self-driving vehicles [138, 173]. While image data provides detailed, high-resolution information, it is expensive to process in time and computational resources, leading to decrease the input resolution [244], which may obfuscate crucial information.

LiDAR sensors provide detailed depth information that is difficult to interpret. The output of a LiDAR sensor: a “point cloud” represents the surrounding environment in 3D space. But these signals are noisy and difficult to interpret: point clouds do not embed the high-level qualitative descriptions that would be useful in diagnosis. The state-of-the-art in LiDAR “understanding” to detect and classify objects, which suppresses depth information.

Neural networks are able to process LiDAR data for single-task classification [127]. For self-driving cars, the single tasks is object detection and labelling. While neural networks are very good at detection and labeling if there is a lot of training data, they also lack the ability to do multiple tasks.

For multi-task classification, neural networks have been lagging. Neural networks can only perform one task, and they do not have commonsense. For example, LiDAR data is useful for tracking objects and describing their *movement.* But object detection and tracking are *separate* tasks: tracking is typically done by another model or process [215]. However, the *type* of object detected and its *movement* or *trajectory* are deeply correlated. Detection and tracking should be incorporated in the same process, along with commonsense. For example, if a skateboard is observed moving near a neighborhood, someone (probably a child) is chasing after it. I show how to interpret sensor data to perform multiple tasks: qualitative object detection and tracking, which is supported with commonsense knowledge.

In this chapter, I present a sensor interpreter that takes a point cloud as input and produces a qualitative description of what it has perceived. This method has been tested exclusively on simulated LiDAR data, but the method is applicable to other sensor outputs, as well. Although the density of the data matters, as described in Section 5.6, this method is a first step towards interpretable, rule-based symbolic interpretation of noisy sensor data.

5.2 LiDAR Sensor Overview

LiDAR is an active remote sensing system. It is a way that autonomous systems can perceive the world[4]. LiDAR works similarly to radar[5] and sonar[6]. The LiDAR unit emits infrared light (also known as "laser beams") and measures how long each light beam takes to come back after hitting a nearby object. The LiDAR unit does this millions of times a second to create a "point cloud": a 3-D map of the LiDAR's perceived world. LiDAR detection range varies, for example, the Luminar[7] LiDAR unit has a 200 meter radius and is used by the Toyota Research Institute[8] and Volvo.

5.2.1 Simulated LiDAR format

LiDAR units are typically placed on the top of vehicles. They emit infrared light at various degrees elevation[9] and azimuth degree. An azimuth is an angular measurement in a spherical coordinate system. Each LiDAR "hit" (the distance in meters to the detected object) has a corresponding degree elevation and azimuth degree.

In simulation, LiDAR data was generated using the same vehicle simulation system described in Chapter 3. The LiDAR output is represented by the keyword `lidar` and is output on the vehicle log every tenth of a second. Each row contains 1980

[4]I argue that the greatest challenge in autonomous driving is perception. In the safety-critical driving environment, robust vision and LiDAR processing is essential. But these systems are brittle, and require careful signal processing.

[5]Radar uses radio-waves to determine the range, angle, or velocity of objects. It is used in ships and air crafts.

[6]Sonar uses sound to determine the range, angle, or velocity of objects underwater. It is used in submarines.

[7]`https://www.luminartech.com`.

[8]Perception Technology for TRI Platform 3.0: https://www.tri.global/news/toyota-research-institute-introduces-next-generation-automated-driving-research-vehicle-at-ces-2018-1-4.

[9]In my work, the LiDAR starts from a neutral degree elevation and rotates down to -10 degrees.

		Degrees Elevation										
		0	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10
Azimuth Degrees	0	N0	N0	N0	46.6	53.4	40	31.9	26.3	22.6	20	18
	2	N0	N0	46.9	46.6	54.1	40.1	31.7	26.1	22.5	20	18
	4	N0	N0	N0	79.6	54.6	40.1	31.6	25.9	22.5	20	18
	6	N0	N0	N0	79.6	54.6	41.1	32.9	25.7	22.5	20	18
	8	N0	N0	N0	79.5	54.7	41.1	32.7	26.3	23.1	20	18
	10	N0	N0	N0	79.4	54.7	41.1	32.5	26.1	23	20.6	18.4
	12	N0	N0	N0	79.3	54.7	41.1	32.5	26	22.9	20.6	18.4
	14	N0	N0	N0	81.6	54.6	41.1	32.6	26	22.9	20.6	18.3
	16	N0	N0	99.7	81.5	54.6	41.1	32.8	26.5	23	20.6	18.3
	18	N0	N0	101.7	81.3	54.5	41	32.8	27	23.2	20.6	18.3

Table 5.1: A raw data table of the LiDAR traces. The LiDAR unit starts at 0 azimuth degrees and emits 11 pulses at 0,-1, ...,-10 degrees elevation for every two azimuth degrees.

values: it reports a value for every 2 azimuth degrees (0,2,4,... azimuth degrees) for 11 degrees elevation[10]. The raw data trace format starts in front of the vehicle at 0 degrees elevation and 0 degrees azimuth. For each azimuth it sends emits 11 pulses at descending degrees elevation (starting at 0-neutral and descending to -10 degrees elevation). From the point of reference of the vehicle, the LiDAR unit rotates clockwise and repeats the process every 2 degrees: it emits 11 pulses at 0,-1,...,-10 degrees elevation. It continues this process until the unit has made a full rotation. A raw data table of values for a subset of one LiDAR row is in Table 5.1. The values are rounded to the nearest tenth of a meter, and a value of `N0` indicates that no object was hit. A full row of data is in the Appendix in Table C.1.

5.2.2 LiDAR format in Collected Data Sets

Nuscenes [31] and other self-driving data sets report LiDAR data as a PointCloud object. The PointCloud object is a list of LidarPointCloud instances: `(x, y, z, intensity)`, where `x, y,` and `z` are coordinates, and `intensity` is the return strength of the laser pulse that generated the point. The `x` direction is left and right, the `y` di-

[10]Since the LiDAR unit is on the top of the vehicle, the degrees elevation start at 0 and point down. So that the elevation is negative.

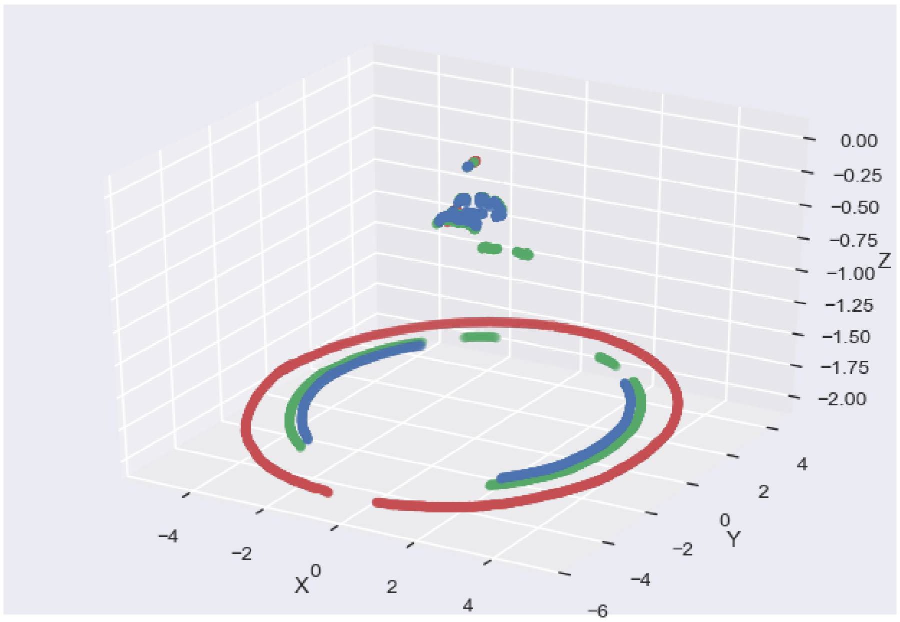


Figure 5-1: The 4th, 5th, and 8th beams of nuScenes LiDAR data for one sample. The 4th beam is in blue, the 5th beam is in green, and the 8th beam is in red. The 8th beam, seen in red, is hitting the ground.

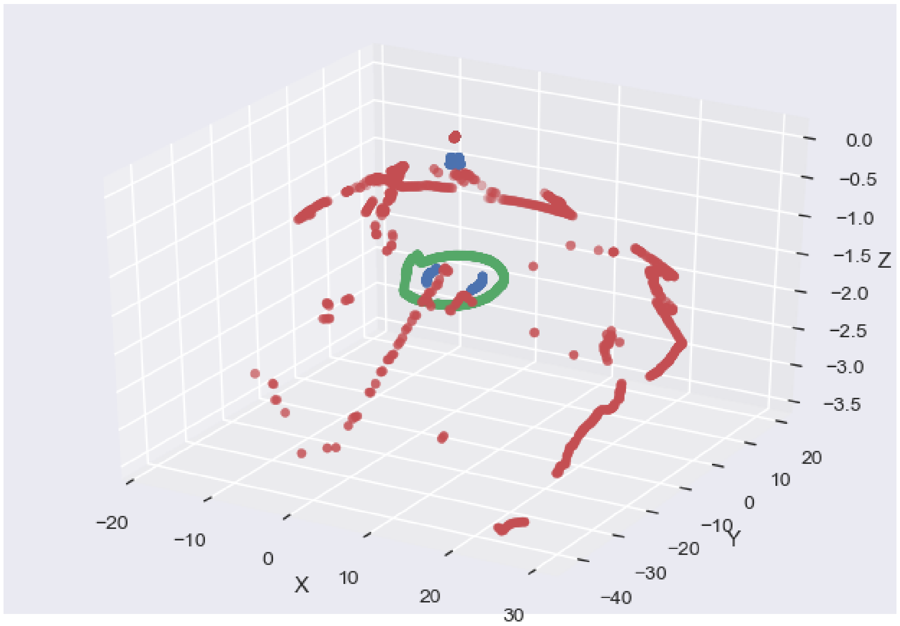


Figure 5-2: The 1st, 10th, and 20th beams of nuScenes LiDAR data. The 1st beam is blue, the 10th beam is green and the 20th beam is red. The first and 10th beam are reflecting off parts of the vehicle. And the 20th beam is too scattered.

rection is front and back, and the `z` direction is up and down. The raw `LidarPointCloud` instance also has a beam number (sometimes called a ring number) which corresponds to the beam which sent out the returned point. The LiDAR unit is located at `(0,0,0)`.

NuScenes uses 32 beams (or rings). Each beam samples a cone around the detector. The axis of the cone is a vertical line. There is a cone for each of 32 altitude angles from -30° (peering down) to +10° degrees (looking up). The beam is rotated around 360° in azimuth, sampling 1084 points at that altitude in each rotation. This results in 34,688 `LidarPointCloud` instances for each timestamp. But, this LiDAR data is noisy, which is shown in Figure 5-1. In red, the 8th beam is a circle in the x-y plane at $z =$ 2 meters. This can be interpreted as hitting the ground, since the origin of the LiDAR unit is on top of the vehicle at `(0,0,0)` and the height of a vehicle is around 2 meters. The average angle of ring 8 is -20 degrees. This makes sense, because the circle is on the ground and the average distance to the ground is -1.77 meters

Some beams are more useful than others. In my analysis, I do not use the early beams (e.g. 1,2,3) and later (e.g. 20+) beams, as illustrated in Figure 5-2. These beams are particularly difficult to understand. In particular, the first beam is too close, hitting the top of the vehicle. The tenth beam hits the ground, and the 20th beam is too far away. The code to generate these visualizations are in the Appendix 16.

The nuScenes LiDAR traces are intended to be visualized with the vision data, as seen in Figure 5-4. In the top-down LiDAR view in Figure 5-3, there is a slight tilt in the vehicle's position. This can also be detected from the difference between the angle on the left of the car and the angle on the right of the car, which I do in my analysis.

5.2.3 Related Work on LiDAR Processing

In the literature, point cloud interpretation is defined as an "object detection" tasks. This detection task is defined as creating a "tight" bounding box around perceived objects. This is difficult due to the amount of noise in point cloud data. One way

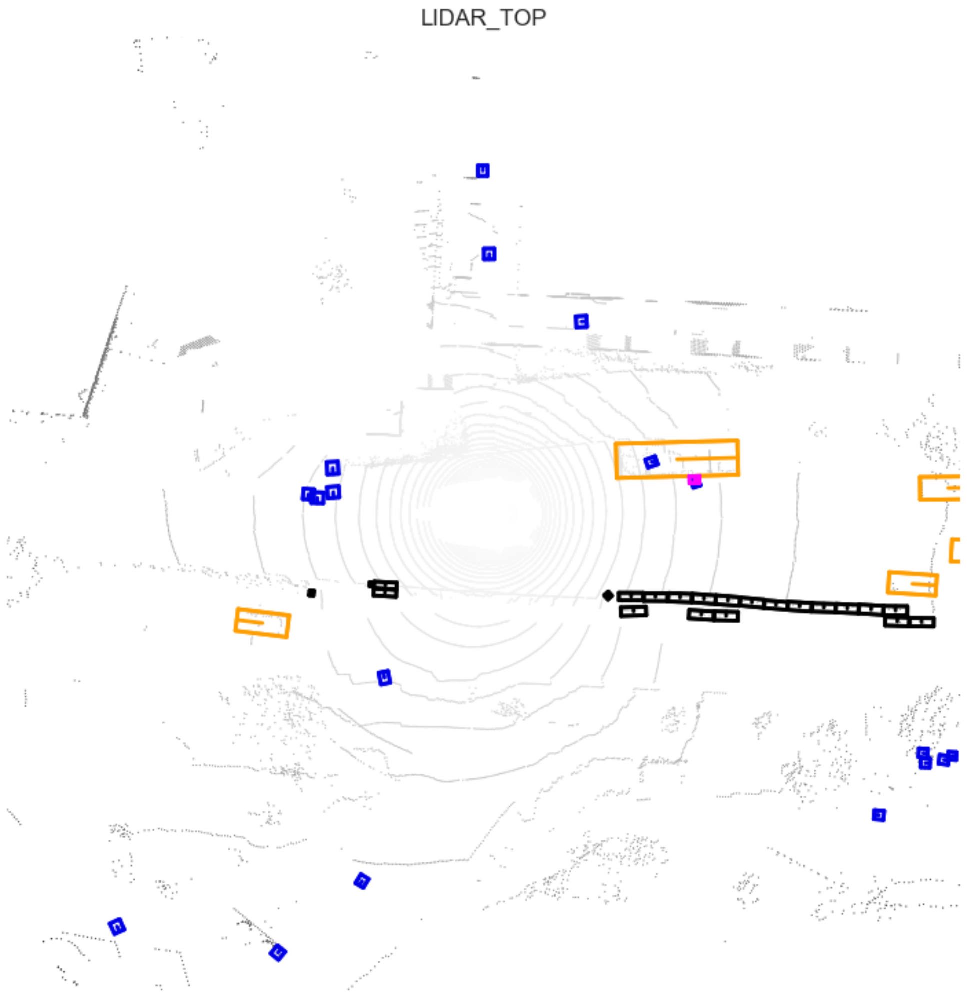


Figure 5-3: A top-down view of all the LiDAR beams.

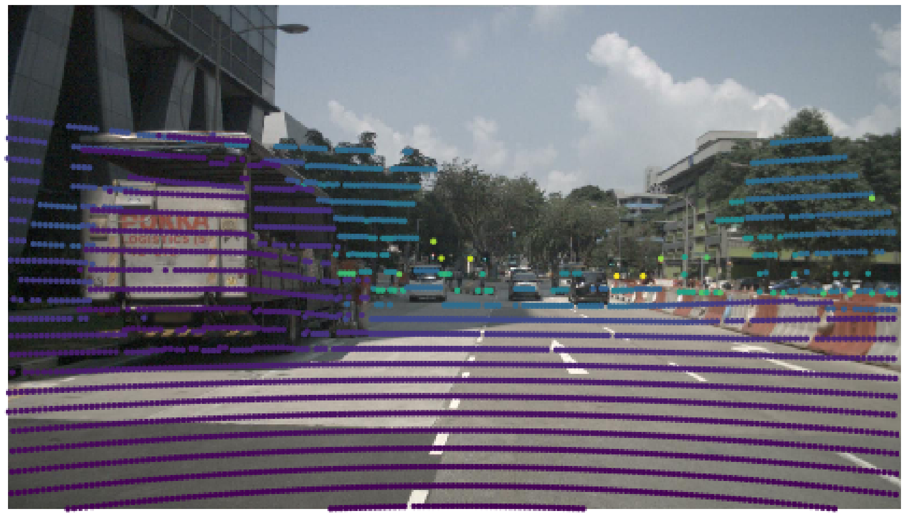


Figure 5-4: A view of all the LiDAR beams on top of the front-facing camera image.

to decrease noise is to supplement LiDAR with vision data. Frustum PointNets [181] uses LiDAR data to expand 2-D image detection to 3D bounding boxes. This is an extension of [182], a unified neural network architecture to segment point cloud data.

I focus on nuScenes because the data set is the most realistic. The nuScenes data set is long-tailed, highlighting the imbalance between common and rare object classes. Although the nuScenes challenges are the “closest” to real-world scenarios due to the data distribution, the challenges do not require abstract thinking[11].

As of July 2020, the top performing algorithms on the nuScenes detection task using only LiDAR [12] were the following algorithms:

1. CVCNET, which is based on Class-based Grouping and Sampling (CBGS) [255], the algorithm used by the third-rank MEGVII team.

2. DTIF, which is developed by Shanghai JiaoTong University (SJTU), but not

[11]The major problem in self-driving is the gap between reality and a vehicle's representation of it. This gap makes it impossible to represent all failure cases in training data (regardless of how “close” that data is to real-world data distribution) and creates the need for anticipatory thinking in autonomous driving. I argue that self-driving challenges should encourage methods that can identify possible failure cases and manage the vehicle's risk exposure to them under the uncertainty in real-world environments.

[12]The real time results on the nuScenes challenge is updated dynamically: `https://www.nuscenes.org/object-detection?externalData=no&mapData=no&modalities=Lidar`. Note that these algorithms only use LiDAR data.

published.

3. The MEGVII team from Tsinghua University that uses "Class-based Grouping and Sampling" (CBGS) [255]. The goal is to extract features from the data (using a 3D convolutional CNN), and then use a class-balanced sampling and augmentation strategy for a more balanced data distribution.

Recently, state-of-the-art methods have been published that outperform the previously mentioned algorithms. CBGS recently outperformed PointPillars [127], which was previously the leading algorithm on the nuScenes detection challenge. Pointpillars is an encoder method, which utilizes PointNets to learn a representation of point clouds indexed by vertical columns, which they call pillars. These features are then incorporated into a 2D CNN architecture for object detection.

Mohammad Sanatkar provided a very comprehensive overview of the state-of-the-art in LiDAR interpretation [196] in a blog post[13]. Most of these methods *combine* vision data and LiDAR data for more data and features in CNN object detection. To my knowledge, my work is the first method to qualitatively understand dense point clouds using edge detection, rather that neural network architectures.

5.3 Method

In order to describe the "point clouds" that a LiDAR sensor perceives, I created thresholds to find "edges," or a cluster of points signaling an object. Thresholds were made on a trial by trial basis that depended on the application, frequency of LiDAR data, and objects in question. I describe this process for detecting vehicles below.

5.3.1 Edge Detection for Object Detection

For my use case, I was interested in detecting vehicles and people. Therefore, I had to define a rule for detecting vehicles, and another rule for detecting pedestrians based

[13]During this thesis work, most of the leading LiDAR interpretation methods were developed in industry and trade-secret. So most of the "cutting-edge" algorithms are described in blog posts instead of academic papers.

on their size in the frame of reference of the vehicle. I focused on these two concepts because the specific motivating problem was to detect errors in parallel parking. For detecting other vehicles, I used simple geometry to figure out how many LiDAR hits (or detections) are necessary to confirm there is a car in front (in the frame of reference of the vehicle). I could also use this information to create a short list of rules to classify the detected objects based on their approximate geometry, and not necessarily rely on training data. This is important especially for objects that may not be present in a training data set. For example, if the autonomous vehicle has never seen a pedestrian walking a bicycle before, it may not be able to classify it, but it will know it's an important "object of interest" because it's wide (~2 meters wide and moving).

5.3.2 Angle Estimation

Simulated LiDAR readings report the distance from the LiDAR indexed by an azimuth and an altitude. In my analysis, I calculated and estimated the angles between successive LiDAR points. I filtered for the edges of successive LiDAR hits, at specific distances (d_1 and d_2) and the angle between them, θ, to classify detected objects. This method is *faster* and *more interpretable* than opaque learning systems that classify objects: the detections and classifications have implicit reasons (e.g., this perceived object is a vehicle because it is 2 meters wide, which is too wide to be a pedestrian, etc.)

This estimation setup is visualized in Figure 5-5. The Law of Cosines, in equation 5.1, shows the relation between the detected distances at the endpoints (d_1 and d_2) from the LiDAR log, and the angle between the edges of that object, θ. Consider if the detected object is directly in front of the simulated (self) vehicle. This is useful for parking and stopping distance estimation. For the remainder of this section, I focus on the use case of parallel parking.

$$x^2 = d_1^2 + d_2^2 - 2d_1d_2\cos\theta \tag{5.1}$$

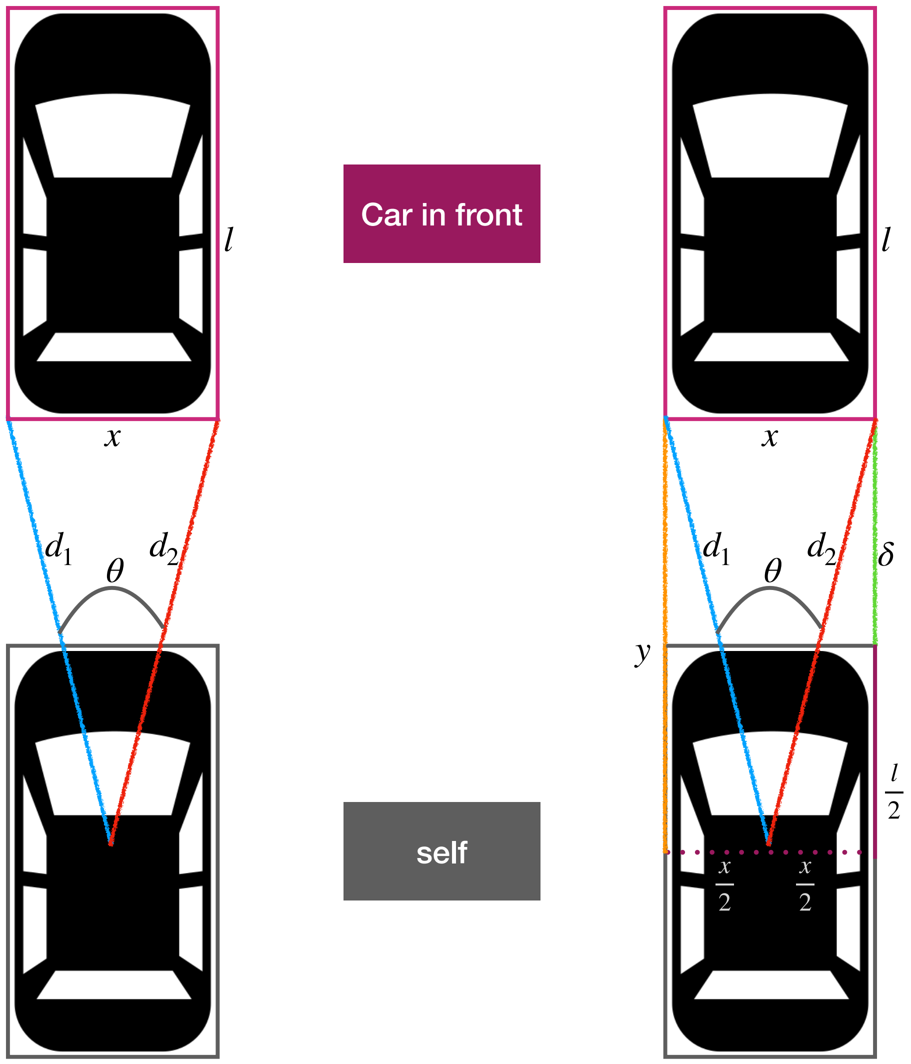


Figure 5-5: The geometric definitions for an object detected precisely in front.

To understand how Equation 5.1 can be used for detecting another car parked in front of the self-driving car, see Figure 5-5, where there is an object detected directly in front of the vehicle. I approximated the number of hits to determine that the object is a vehicle at various distances by using: $\cos^{-1}\theta = 1 - \frac{x^2}{2d_1^2}$, where x is the approximate width of the object in front. I assume that the LiDAR unit is in the middle of the vehicle[14]. Then if the estimated width, x, is hypothesized to be the width of a standard vehicle, and l is the length of a standard vehicle, let $x = 2$ meters,

[14]This is a fairly good estimation, as most LiDAR units are mounted on the top of the vehicle, showing a global view of the LiDAR traces radiating from the center of the vehicle. An example of this "global" LiDAR view is at the end of this chapter in Figure 5-9

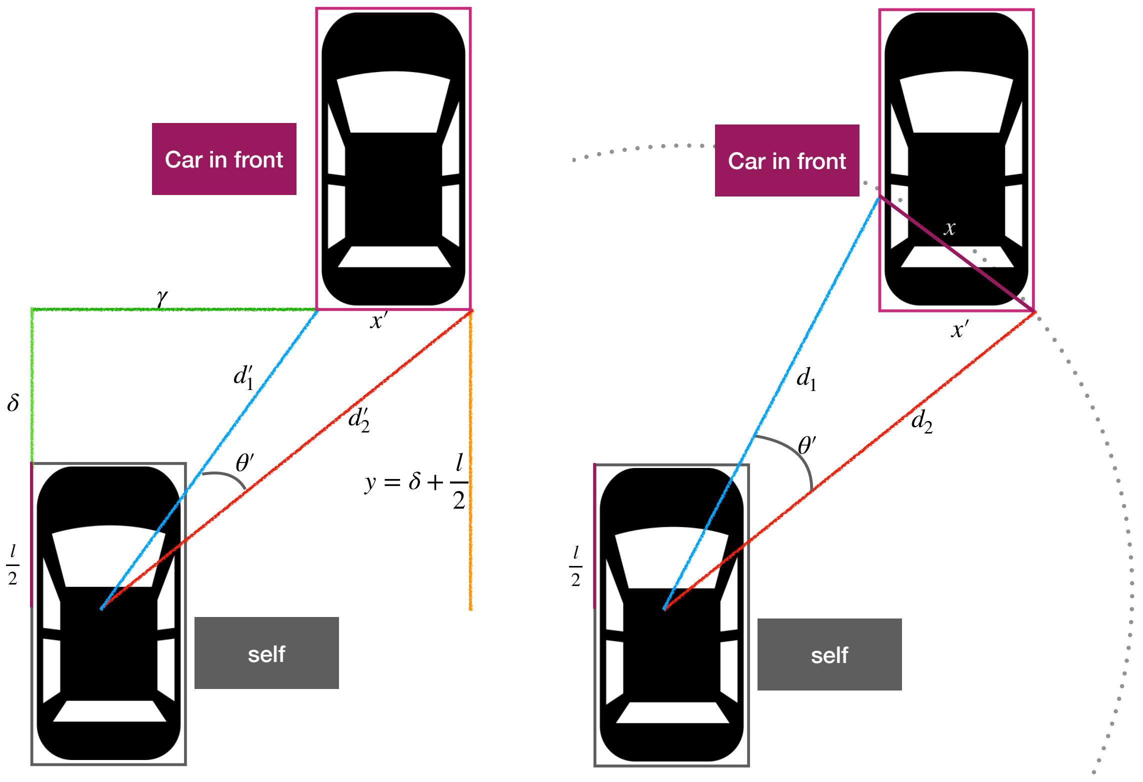


Figure 5-6: The geometric definitions for a vehicle detected to the front and to the side. The precise setup is shown on the left, and the estimated definitions are shown on the right.

and $d_1, d_2 = 4$ meters to get $\theta = .505$ radians = 29.0 degrees.

This is an educated *estimate*. While the exact number of hits depends on the scale of LiDAR hits, the conclusion is that I will need to have about 29 degrees of consistent detections to be confident in the detection of a standard vehicle at 4 meters distance from the vehicle (at the edges).

Zoe Liu and I extended this analysis for general parallel parking scenarios [146]. Consider if the vehicle is not directly in front, but to the side, as seen in Figure 5-6. Using the same equation, I get an estimate for x', the chordal distance between d_1 and d_2 at angle θ. Since I was focused on *estimating* this distance, I choose to use the same equation, and let $x' \approx x$. For my scenarios, this worked well, especially because the rules are in specific ranges corresponding to qualitative values; so the exact measurements need to only be estimated.

Note that x can be more precisely estimated from x', d_1' and d_2': the corners of the object, classified by the *nearest* detection. But, this is not always feasible, especially when there are *multiple* objects detected, as is typical in most urban, self-driving environments. This may be explored in future work.

5.3.3 Object Tracking: Describing Movement

Once an object has been detected, tracking movement of objects from the simulation is straight forward. A propagation model is used with a set a rules that define qualitative `movement` changes, which is describe in Chapter 3. The first step is alignment: finding the detection of the *same object* that moves across a scene. This is done by collecting the object detection across snapshots and qualitatively describing the movement across several seconds.

5.3.4 Parking Rules

The use case to evaluate this LiDAR interpreter is a parallel parking scenario, shown in Figure 5-8. This scenario was chosen because it relies on LiDAR information, concrete rules, and it extends the work in Chapter 3.

I defined the minimum space needed by Equation 5.2 [25]. Let *self* be the vehicle doing the parking, where l = length of the self vehicle, x = width of the vehicle in front, k = distance from the front wheel to the front of self, b = the length of the car's wheel base, and r is the radius of the vehicle parking's curb-to-curb turning circle. These are shown in Figure 5-7 and the equation for minimum space needed is given by Equation 5.2.

$$\text{minimum space} = \sqrt{(r^2 - l^2) + (l + k) - \left(\sqrt{r^2 - l^2} - x\right)^2} - l - k \tag{5.2}$$

The parallel parking rules can be expressed as following four thresholds (and an optional fifth threshold).

1. Minimum space needed: threshold given by Equation 5.2.

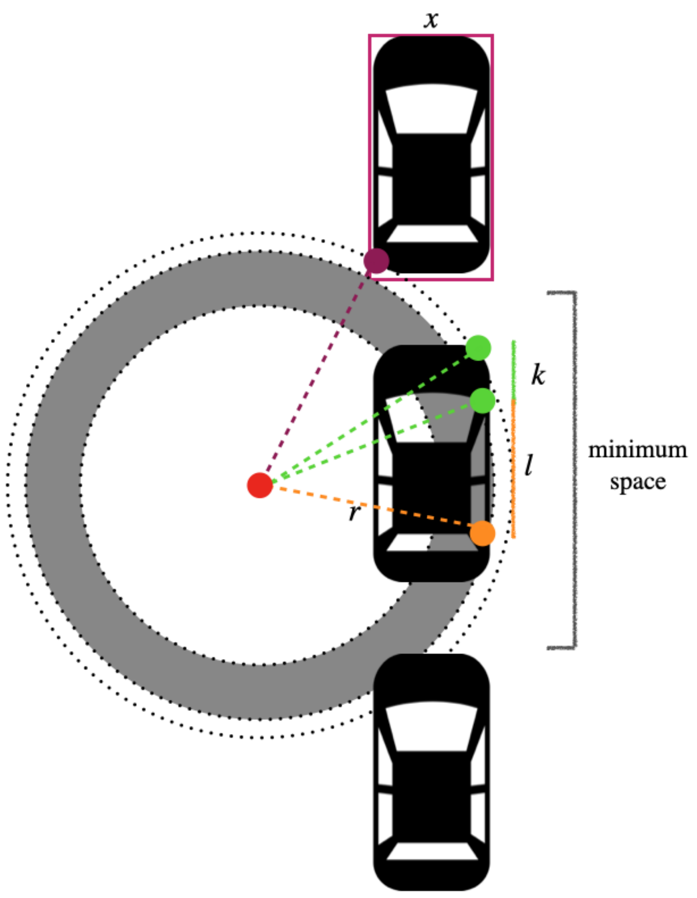


Figure 5-7: Visual diagram for the variables for the parallel parking scenario.

2. Backup threshold: the distance between the front of our car and the back of the car we are aligned with.

3. Turning threshold: theta between our right front wheel and the back left wheel of the car we are aligned with (r = radius of our car's curb-to-curb turning circle).

4. Straightening out threshold: theta between our right back wheel and the horizontal

5. (OPTIONAL) Driving forward threshold: optional, minimum space needed - the length of our car.

Screen shots of these stages are seen in Figure 5-8. Note that checking whether there is enough space to park is done as the car approaches a potential parking space. After the thresholds have been validated, the parking process is completed in three steps:

1. Approach: bring vehicle to the front of the parking location.
2. S curve: reverse into the space in an "S" shape.
3. Straighten out: once vehicle is in the space, pull forward evenly.

The calculations, using the propagator system [184] is in the Appendix in Listing 13.

5.4 Experiment Results

In order to validate this LiDAR interpretation method, I used simulated log traces, similar to the ones generated for ex post facto explanations [75]. Because of the manual controls necessary to run the simulations: an operator had to control the vehicle in simulation, I focused on a few scenarios targeted at describing the LiDAR behavior for parallel parking scenarios.

5.4.1 Simulated LiDAR challenge scenarios

The main challenge scenarios were parallel parking logs, which was joint work with collaborator, Siyu (Zoe) Lu [146]. Example outputs for each operation and for the whole parking process are split into four parts.

The process checks if there is enough space to park. This is done by measuring distances and checking it against the minimum parking distance; Equation 5.2. The explanatory results for a safe parallel park are shown below:

```
(explain-readable distance)
REASON: The car length exceeds the minimum space needed for parking.
          Consistent with the Lidar data.
```

The second step of parking process checks the S-curve behavior. This is performed in two steps. First, it is confirmed that the vehicle backs up:

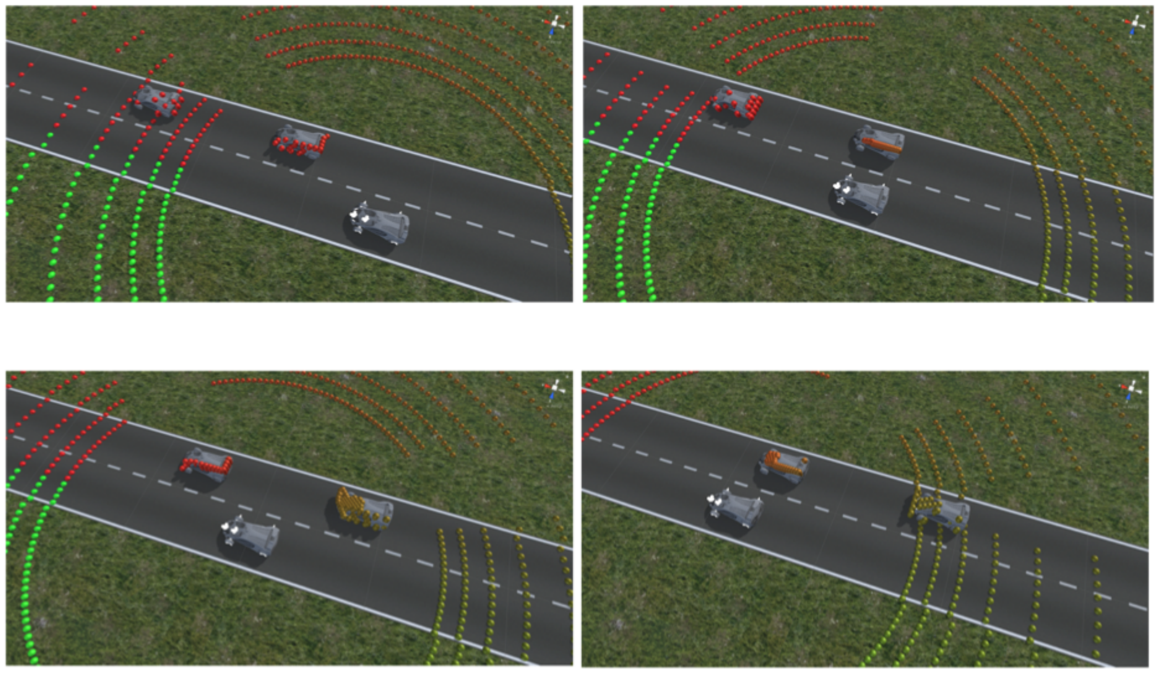


Figure 5-8: Screenshots of the four stages of parallel parking from the Unity game engine.

```
(explain-readable wheel-acceleration)
REASON: Front wheels and rear wheels accelerated backwards.
                  Consistent with the steering wheel and accelerometers.
                  Since the forward acceleration of the car is negative,
               the car MUST HAVE backed up.
```

The second step of the S-curve makes sure that the correct motions took place to complete the action:

```
(explain-readable wheel-acceleration)
REASON: Front wheels and rear wheels accelerated backwards AND
                  Left wheels accelerated more than right wheels.
                  Since the forward acceleration of the car is negative,
                  the car MUST HAVE backed up.
                  Since the magnitude of acceleration of left wheels are
              larger than the magnitude of acceleration of right wheels,
               the car MUST HAVE turned in.
```

And at the end, successful parking is verified and explained:

```
(explain-readable parking)
REASON: Regular parking process within all thresholds.
                  Since the car has backed up, turned in, straightened out,
                  and driven forward within thresholds,
               the car MUST HAVE parked safely.
```

There are also examples of unsuccessful parking. This is one example of an error during the backup (first step in the S-curve procedure):

```
(explain-readable parking)
REASON: Error in backing up.
   Since the position of the car before and after backing up exceeded
   the backup threshold,
                the car MUST HAVE made an error in the backup step.
```

5.4.2 Data Set LiDAR Challenge Results

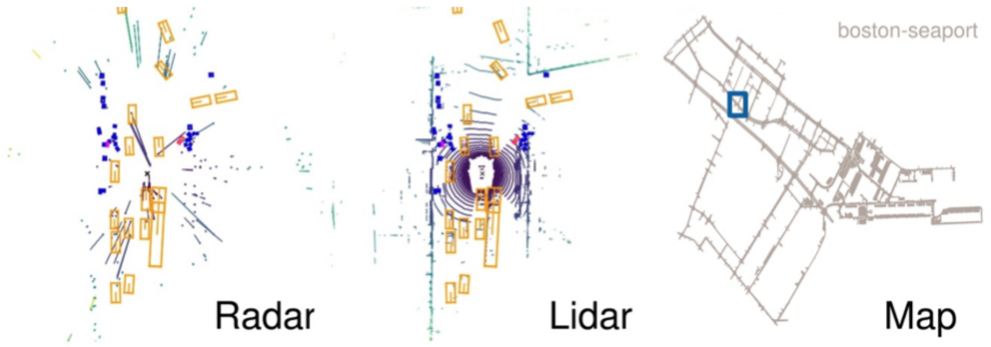


Figure 5-9: Various sensor outputs for a nuScenes scene snapshot.

The task to interpret LiDAR in collected data sets is different than the parallel parking example. In this task, I was interested in *qualitatively describing* LiDAR traces. Figure 5-9 shows various sensor outputs that are difficult to interpret. The labeled outputs is "Pedestrian with a pet, bicycle, car making a u-turn, lane changes, pedestrian crossing in a crosswalk." The task is to *interpret* LiDAR point clouds and output a qualitative description.

The first step is to separate the LiDAR point clouds into distinct objects. This is done with edge detection, as described in Section 5.3.1. However, this method changes for the scale of collected LiDAR data[15] for two reasons.

1. Edge detection is applied for each beam or ring. The early beams are disregarded, as the points reflect off the top of the car, as seen in Figure 5-2. Similarly, later beams are also disregarded as they reflect off the ground. The width of an object is the edge length of the earliest beam. The depth is calculated by finding the last beam where the object of "similar" length was detected. This method succeeds in finding about 50 percent of all the objects in a scene. The method fails on objects that are far away, multiple objects being classified as a single object, and due to the lack of non-hit points. Down sampling will be revisited in future work, although initial attempts failed.

2. Collected data sets are quite dense; in a single snapshot or scene, there are very few "non-hits," or `LidarPointCloud` points that do not hit any object. The number of non-hits in a scene is between 40-50 points. Therefore, I could not apply edge detection directly, since nearly all the points are continuous hits.

Due to the difficulties in applying the method directly, an intermediate "bounding-box" method was used. "Bounding box" methods or "object detection" methods for point cloud data, are used to generate a tight box around objects. These methods are described in Section 5.2.3. The nuScenes data set has metadata for these bounding boxes in each annotated object, as the `size` property, seen in Figure 5-10. These boxes are then qualitatively described using threshold rules for size, location, and movement (by tracking the object across a scene).

```
movable_object.trafficcone
[1345.3609354399998, 3926.40104428, 2.15223104]
```

[15]In simulated data, there are 1,980 points per snapshot, and in collected data sets, there are 34,688 points per snapshot.

```
{'token': 'ef63a697930c4b20a6b9791f423351da',
 'sample_token': 'ca9a282c9e77460f8360f564131a8af5',
 'instance_token': '6dd2cbf4c24b4caeb625035869bca7b5',
 'visibility_token': '1',
 'attribute_tokens': ['4d8821270b4a47e3a8a300cbec48188e'],
 'translation': [373.256, 1130.419, 0.8],
 'size': [0.621, 0.669, 1.642],
 'rotation': [0.9831098797903927, 0.0, 0.0, -0.18301629506281616],
 'prev': '',
 'next': '7987617983634b119e383d8a29607fd7',
 'num_lidar_pts': 1,
 'num_radar_pts': 0,
 'category_name': 'human.pedestrian.adult'}
```

Figure 5-10: The nuScenes metadata for an annotated object.

```
Visibility: {'description': 'visibility of whole object is between
80 and 100%', 'token': '4', 'level': 'v80-100'}
Global translation is [410.066, 1196.767, 0.656]
Relatively close to the vehicle, located in the back, to the right.
```

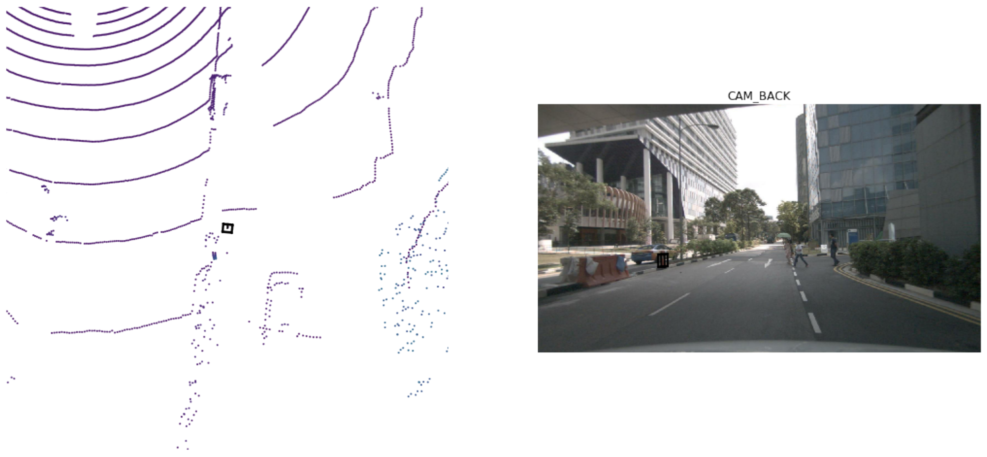
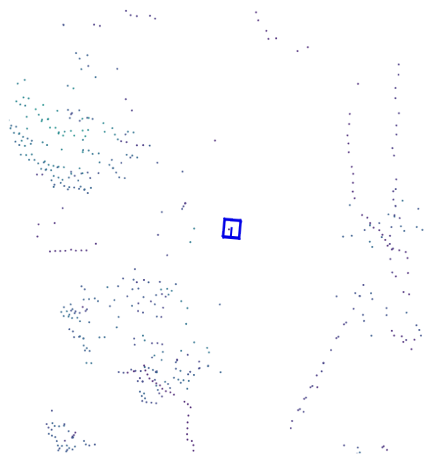


Figure 5-11: A visualization of a raw data and bounding box for a traffic cone behind the vehicle.

The following are a few examples of the qualitative descriptions for the nuScenes data, with visualizations of the scene.

- Figure 5-11 is qualitatively described as "behind, to the right, short, not mov-



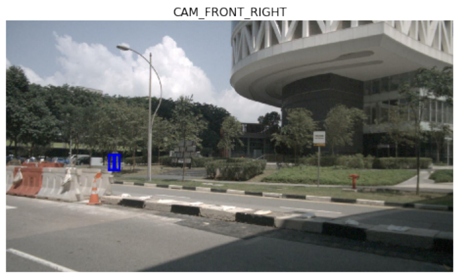


Figure 5-12: A visualization of a raw data and bounding box for a pedestrian.

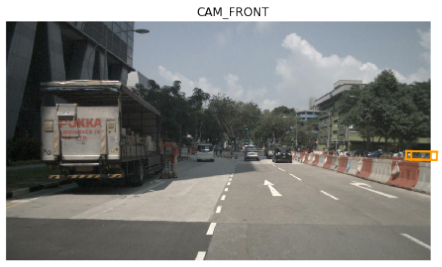


Figure 5-13: A visualization of a raw data and bounding box for a vehicle.

ing." Note that this object is described to the right, although it appears in the left of the photo. This is because it's detected in the rear-facing camera.

- Figure 5-12 is qualitatively described as "to the right, far away, small, slowly moving."
- Figure 5-13 is qualitatively described as "to the right, somewhat close, long and deep, not moving."

5.5 Applying Sensor Interpretation

This sensor interpretation should be able to be applied directly to various sensor outputs. The following parts may need to be tuned for different applications.

1. Edge detection: As described, the edge detection method cannot be directly applied to a `LidarPointCloud` data type. In other applications where the sensor data is especially dense, this method may have to be re-defined.
2. Qualitative Rules: The qualitative descriptions are output from a set of rules and thresholds. I qualitatively describe size, location (in terms of the vehicle), and movement. Other qualitative descriptions will have to be defined.

5.6 Limitations

LiDAR data has changed drastically in the last few years. Firstly, the number of LiDAR hits has increased by orders of magnitude. This results in the density of the LiDAR point cloud to increase, as shown in Figure 5-14. But the increase in LiDAR points also adds to complexity in processing. It is no longer possible to use geometry estimations to detect object sizes. Firstly, since there are more LiDAR points, the resulting point cloud is noisy and the edges of objects are not easily detected. Secondly, with more LiDAR points, there are more false detections: due to noise and because of the density of points, close-by detection are grouped together.

When I tested the sensor interpreter on current-scale LiDAR, it described groups of objects together.

The threshold for determining which points come from the same object is a difficult task. The majority of successful algorithms are deep neural networks [127], which create approximate bounding boxes around objects. Because these bounding boxes are fairly accurate, I instead, describe these bounding boxes on LiDAR data. For example, I use this approach to describe the nuScenes [31] LiDAR data in Chapter 7.

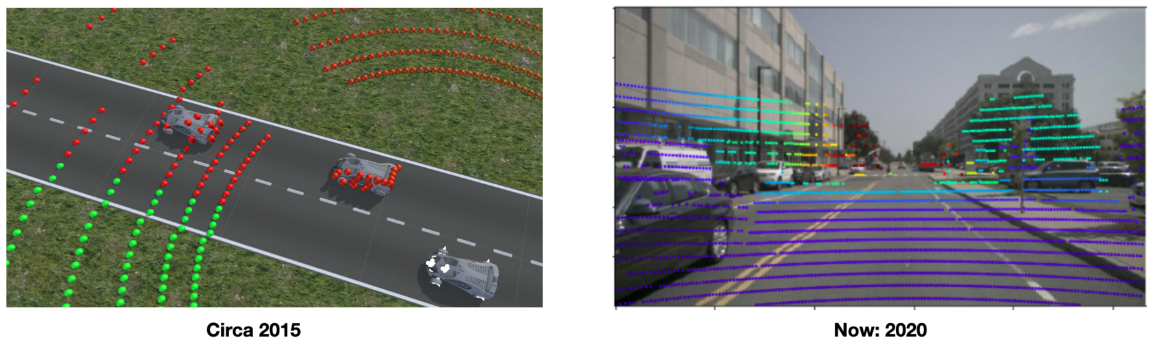


Figure 5-14: LiDAR density between 2015 and 2020.

5.7 Contributions

In this chapter, I showed how to symbolically describe point clouds. This analysis relies on complex geometric and physical rules so that the vehicle's LiDAR component can describe what it is perceiving. I showed how sensor interpretation can be incorporated into ex post facto explanations to justify parallel parking maneuvers. I also showed preliminary results on LiDAR data from nuScenes. This is ongoing work in sensor interpreter. I showed the difficulty in applying my method directly to point cloud data. In future work, I will explore how to directly apply this analysis to modern-scale LiDAR data.

Chapter 6

Learning from Explanations

"But surely to understand must involve the formation of a descriptive plateau of knowledge lying somewhere between raw, totally unprocessed data and detailed answers to problems."[238]

– Patrick Henry Winston

Rule-based systems are interpretable and explainable, but they are time-consuming to create and maintain, since rules are generally hand-coded. In this chapter, I present a method to learn symbolic rules from ex post facto explanations for autonomous vehicles. My method is able to learn that certain explanations and behaviors are exceptions to existing rules, and other explanations and behaviors suggest the need for new rules. These rules can be integrated into an existing monitoring system to detect and explain anomalies, with limited augmentation to an existing system. I evaluated my method on a small self-driving car, a custom MIT RACECAR [39], and I discuss how rules can be used to infer constraints of reasonable behavior in other complex environments.

There are two contributions in this chapter. First, I show a new *application*: I apply reasonableness monitoring to machine *actions* instead of machine perception. Secondly, I build upon the reasonableness monitoring system to make it more *dynamic*: I add a rule-learning method so that rules can be added, augmented, and retracted. This work contributes to "closing the loop" on explainability, where the output explanations are used to improve and learn reasonableness rules in new contexts and environments.

6.1 Introduction

Autonomous vehicles are susceptible to failures. There many ways to "fool" an autonomous vehicle [11], and the failure cases cannot be enumerated[1]. There have been developments towards test suites of plausible failure modes [223][2]. But creating "better" failure detection techniques is not enough. The underlying systems need the capability to *introspect* about their own behavior and learn through experience. For example, in the Uber self-driving accident, a software system ignored the pedestrian detected by the LiDAR sensor to be a false positive detection, resulting in a pedestrian fatality [151]. The software system lacked the commonsense necessary to know that an object moving in the middle of the road is likely a pedestrian. The autonomous vehicle should *learn* from this mistake and ensure it will not be a repeated failure.

Human drivers are also susceptible to failures. But human drivers fail differently than autonomous drivers. Human drivers are able to adapt to driving in new environments. Humans learn new driving rules by examining context and reflecting on their behavior: they explain the best action or alternative to themselves. Take for example, the behavior of "flashing high beams." Based on the location, context, and social rules, we may apply an existing rule (if a neighboring car is flashing their high beams, then turn on the vehicle's headlights), or we may create a new rule based on a new explanation (e.g. since they are flashing their high beams aggressively, that means to watch out for something).

In this chapter, I present a rule-learning method that is inspired by the way that humans learn to drive. I show how to enhance autonomous driving systems with a *dynamic* reasonableness monitor that can learn from explanations of perceived errors that are clearly wrong. My rule-learning method is validated on a real-world robot:

[1]Some examples are security hacks, adversarial attacks and lack of commonsense knowledge, which are detailed in Chapter 7.

[2]Recall from Section 1.1, that an error is a technical mistake and a failure has consequences.

a custom MIT RACECAR[3] built by Tianye Chen [39]. I tested the method on new "traffic light" patterns. The rule-learning system is able to add new rules and behaviors when a new circumstance is repeatedly observed and explained.

6.2 Method

My method extends the adaptable reasonableness monitoring framework [78] to robotic actions. The contribution of this method is two-fold. Firstly, I demonstrate that reasonableness rules can be *learned* by processing and querying explanations of intended vehicle actions. Secondly, I validated this approach on a real system: an MIT RACECAR.

6.2.1 Monitoring Architecture

The reasonableness monitoring architecture consists of rules (constraints), a log data ontology with system state information, a commonsense knowledge base, and a reasoner which constructs explanations. The input to the system is a proposed action and the system state.

```
[(red after green), 'Given']
[(cone isLocated right), 'Given: perception']
[(self isMoving true), 'Given: system state']
...
[(red means stop), 'Commonsense']
...

[(red indicates stop),
    'Rule triggered: driving rule']
```

Listing 6: A subset of the facts that are used in the explanation generation process. The final explanation is that even though the vehicle is moving, and it had perceived a green cone (light), the next cone (light) is red and the vehicle should stop.

The proposed action is parsed and supplemented with commonsense data. This data is forward-chained on a set of reasonableness rules to produce more data. With

[3]MIT RACECAR: `http://racecar.mit.edu`.

```
from afinn import Afinn
afinn = Afinn()

>>> afinn.score('I saw a yellow light and nothing good happened')
3.0
>>> afinn.score('I saw a yellow light and nothing bad happened')
-3.0
>>> afinn.score('I saw a yellow light and nothing happened')
0.0
>>> afinn.score('I saw a green light')
0.0
>>> afinn.score('red appeared after green')
0.0
>>> afinn.score('I saw another car')
0.0
>>> afinn.score('I saw another speeding car')
0.0
>>> afinn.score('I saw a car run a red light')
0.0
```

Listing 7: Examples of the sentiment scoring on vehicle explanations.

this comprehensive set of data (or facts) as evidence, the action is deemed to be reasonable or unreasonable and an explanation is provided. The explanation is a chain of `facts`: a symbolic triple with an associated *reason*[4]. An example explanation in is Listing 6. With a natural language generation (NLG) template, the explanation can be shown to a user in readable text.

6.2.2 Rule Learning

My rule-learning system integrates into the adaptable reasonableness monitoring prototype [78]. The rule learning system processes an error text file: it parses the explanations and state at the time of the error (time, system state, sensor data, etc). After aggregating together this information, the rule learning system judges whether the explanation in the log data and system state should constitute a new rule, or whether it is an exception to an existing rule. The system determines this

[4]Note that each fact has a triple and a reason. They are stored in a `pandas DataFrame` object, which includes an index for each fact.

by examining the sentiment of the explanation, and it checks if any of the errors are similar to each other. If any of the errors happen multiple times. If there is more than one instance, then it uses the error information to create a new rule.

The sentiment analysis determines whether a new rule should be learned. For the self-driving domain, I used an existing model [172, 90] that scores the sentiment of the explanation text in a range from -5 (very negative sentiment) to 5 (very positive sentiment). Most of the explanations that I used were *neutral* with a score of 0, shown in Figure 7, so I grouped neutral and positive scores together. Any explanation with a neutral or positive score is created as a new rule. Note that sentiment analysis is an open problem, and the *accuracy* of this analysis is out of scope of this chapter.

A new rule is created by parsing the error log text. The rule learner looks for specific symbolic relations in the error explanation, for example, “before,” “after,” “because.” If it finds any of those symbolic relations, it then processes the text before and after that word for the rule binding. This creates a symbolic triple, composed of the text before the keyword, the keyword itself, and the text after the keyword. This triple is used in the new rule text, which is output into the AIR rule Language. The end result is a new Air rule, written in N3 that is appended to the existing rule file in the monitoring system.

6.2.3 RACECAR Architecture

The real-world robotic system for validation is a custom, Traxxas Slash RC racing car, modified to include a JetsonTX2, a Hoyoku lidar, a ZED stereo camera, a inertial measurement unit (IMU), and a VESC based motor controller[5]. ROS Kinetic runs on the JetsonTX2 and takes care of the computation and planning decision making for the vehicle.

A stereo camera on board is used to detect cones and place them on the map accordingly. The camera images are processed at a rate of 5hz, the car drives slowly. The experiment relies on the camera’s detection of cones straight ahead. Therefore, I removed the top and bottom third of the image, as cones could not possibly appear

[5]`https://vesc-project.com/`

above the ground or be blocking the car. The image is converted to HSV values and masked using empirically tested red, green and yellow thresholds to find and locate the cones in the image. If a contour is found, the distance and angle from the car is calculated using the left and right images of the car.

6.3 Experiments

The main goal of the experiment was to validate the rule learning system with various traffic light scenarios with and without errors. There are three possible scenarios for traffic light transitions: red to green, yellow to red, or green to yellow. I generated five sequences for each type of sequence and allowed the RACECAR to drive through the given course three times, which generates a sum total of 45 tests.

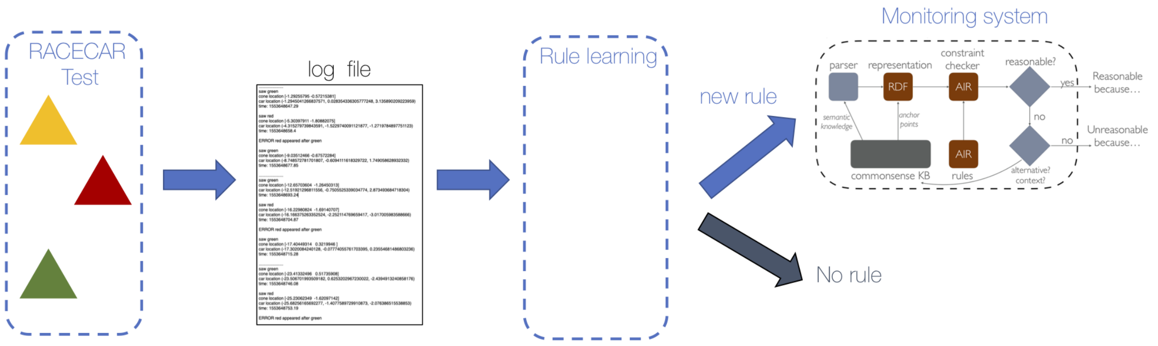
Test type	Sequences	Ground Truth	System
error	5	exception	no rule
normal	5	reasonable	no rule
repeat	5	new rule	new rule

Table 6.1: A table of the 15 distinct sequences that were tested on the RACECAR platform. The error logs had specified errors, which are deemed exceptions to the rule and so no new rules are made. Normal tests were explained to be reasonable, and so no new rules are made. Repeated errors are explained and so new rules are made, as expected.

6.3.1 Experiment Design

The experiment was performed in a lab basement with cones four feet apart from each other. I used three cone colors: red, yellow, and green, corresponding to existing traffic lights. My goal was to validate the monitor's rule learning ability on new cone sequences, to mimic new traffic light sequences. For example, traffic light sequences typically use "yellow" as a transition from green to red (i.e. green, yellow, red). This is important to monitor because there are different light patterns in different contexts[6].

[6]It has been shown that AVs learn patterns not meaning: `https://medium.com/@swaritd/red-means-stop-traffic-lights-for-driverless-vehicles-f972b14990e3`. AVs cannot simply memmorize these mundane light patterns



```
saw green
cone location [-1.29255795 -0.57215381]
car location (-1.2945041266837571, 0.028354336305777248, 3.135890209223959)
time: 1553648647.29

saw red
cone location [-5.30397911 -1.80882075]
car location (-4.315279739843591, -1.5229740091121877, -1.2719784897751123)
time: 1553648658.4

ERROR red appeared after green

saw green
cone location [-9.03512466 -0.67572284]
car location (-8.748572781701807, -0.6094111618329722, 1.749058628932332)
time: 1553648677.85

saw green
cone location [-12.65703604 -1.26450313]
car location (-12.51921296811556, -0.7505525339034774, 2.873493684718304)
time: 1553648693.24

saw red
cone location [-16.22980824 -1.69140707]
car location (-16.166375263352524, -2.252114769659417, -3.017005983588666)
time: 1553648704.87

ERROR red appeared after green

saw green
cone location [-17.40449314 0.3219946 ]
car location (-17.3020084240128, -0.07774055761703395, 0.23554681486803236)
time: 1553648715.28

saw green
cone location [-23.41332496 0.51735908]
car location (-23.506701993509182, 0.6253202967230022, -2.4394913240858176)
time: 1553648746.08

saw red
cone location [-25.23062349 -1.62097142]
car location (-25.68256165692277, -1.4077589729910873, -2.076386515538853)
time: 1553648753.19

ERROR red appeared after green
```

Figure 6-1: A flow diagram of the experiment design. The RACECAR system outputs a log file after a running through a specific sequence of cones. That log file is then processed by the rule learning system, which either creates a new rule for the existing monitoring system, or not In the case of a normal test run no rule is made.

There were 15 unique sequences of cones that were tested. For each sequence, the RACECAR is navigated around all of the traffic cones in a single cone sequence. The log file is saved and the process is repeated for each sequence. This experiment flow process is demonstrated in Figure 6-1.

A test breakdown of the different cases are seen in Table 6.1. I tested for three different types of behaviors. The first test sequence was with errors specifically introduced. The second test sequence were normal sequences without errors. The third test sequence were repeated behaviors that would trigger errors in the log, but should be learned as new rules.

The RACECAR is connected to a game joystick, and the R1 button gives control of the VESC motor controller to the autonomous system. When the button is not pressed, the joystick sends a command of 0 speed to the VESC. This is to ensure the safety of the car as the testing area is an active hallway with foot traffic. The car is in autonomous control when it navigates around cones. When it completes a set of cones representing a traffic light, the R1 button is released to signal to the system that it has completed a single traffic light and to reset it's queue of light sightings for the next traffic light

6.3.2 Experiment Results

The RACECAR was able to navigate through the cones successfully and detect errors as they occurred. At times the RACECAR erroneously detected a cone twice, but that did not significantly affect the experiment, as it is valid to see the same traffic light color more than once. The error does not induce an unwanted transition error. Example log files from each of the runs can be found in Figure 6-2 The error log is fed into the rule learning system [78] and the resulting rules are integrated into the monitoring system. The output rules for the corresponding log can be seen in Figure 6-3.

The rule learning system output corresponds to the repeat error log listed Figure 6-2. The rule learning system found the repeated transition errors and created a new rule that green can be expected to come after yellow. The rule learning system was able to successfully detect the recurring light transition errors in each log and update the rule file in the monitoring system.

6.3.3 Challenges

This work focused on building and using the RACECAR platform to evaluate the performance of anomaly detection in autonomous vehicles based on symbolic rules and reasonableness. A far more expansive set of rules can also be applied to the car's behavior and observations. The set of rules should originate from a driving handbook, which details the literal rules set for the vehicles on the road. Additionally, given that autonomous vehicles interact with other vehicles and it would be interesting to apply the anomaly detection and adaptable monitoring system to an autonomous vehicle in the presence of other possibly non-autonomous vehicles.

```
.....................
saw green
cone location
[-1.29255795 -0.57215381]
car location
(-1.2945041266837571, 0.028354336305777248, 3.135890209223959)
time: 1553648647.29

saw red
cone location
[-5.30397911 -1.80882075]
car location
(-4.315279739843591, -1.5229740091121877, -1.2719784897751123)
time: 1553648658.4

ERROR red appeared after green

saw green
cone location
[-9.03512466 -0.67572284]
car location
(-8.748572781701807, -0.6094111618329722, 1.749058628932332)
time: 1553648677.85

.....................
saw green
cone location
[-12.65703604  -1.26450313]
car location
(-12.51921296811556, -0.7505525339034774, 2.873493684718304)
time: 1553648693.24

saw red
cone location
[-16.22980824  -1.69140707]
car location
(-16.166375263352524, -2.252114769659417, -3.017005983588666)
time: 1553648704.87

ERROR red appeared after green
```

Figure 6-2: A subset of a repeated error log.

```
The following events are repeats and should
be new rules.
Found the explanation
  ERROR red appeared after green
Found triple ['red', 'after', 'green']

:added-rule-1 a air:Belief-rule;
  air:if {
      foo:red ontology:after foo:green. };
  air:then[
    air:description
      ("ERROR red appeared after green");
    air:assert[air:statement{foo:cone
      air:compliant-with
      :learned_policy .}]] ;
  air:else [
    air:assert[air:statement{foo:cone
    air:non-compliant-with
  :learned_policy .}]] ;
```

Figure 6-3: The output of the rule learning system for the repeated error in Figure 6-2 that should be parsed into a new rule. The resulting rule text is appended to the rule file and updated in the monitoring system.

6.4 Applying Rule Learning

The results presented are for a *specific* hardware robot in a *simplified* real-world environment. In this section, I outline the requirements to apply this methodology to a new hardware specification, task, or domain. This methodology is designed to be incorporated with the reasonableness monitoring system. For an arbitrary system, rule-learning can be applied as long as these constraints are met:

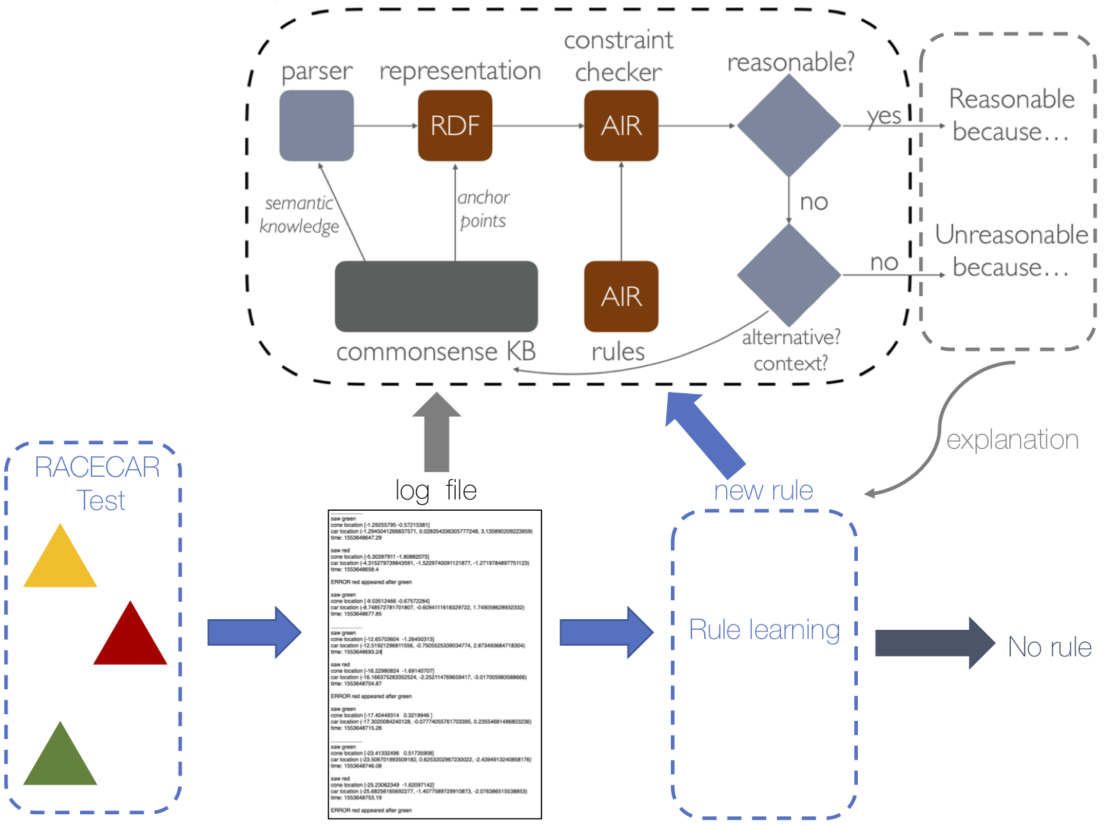
- Data: The system being monitored needs to be able to log its system state. An ontology for the log needs to be defined.
- Monitoring system: The system should be wrapped in a reasonableness monitor. This requires an ontology for data (described above), and reasonableness rules.
- Explanation "evaluation": The rule-learning prototype needs a given metric to determine what is anomalous or not. In the autonomous driving domain, I used a sentiment score that ranked whether the explanation had a dangerous or erroneous sentiment.

6.5 Limitations

The traffic light experiment presented here is a simple example of how anomaly detection coupled with a rule updating framework could work together in real life to inform the car of unreasonable and strange sightings. However, to be applicable to the complex series of actions and language for autonomous vehicles, the system will need a human-in-the-loop for verification.

The explanation "evaluation" for the RACECAR application is oversimplified. It does not utilize the contextual information from the vehicle's state and surroundings in making the decision as to whether or not to add the rule to the rule set. Adding context to each anomaly helps explain why the rule was broken. For example, one rule of the road states that vehicles shall not drive through red lights. However, if a car happens to observe multiple times that an emergency vehicle drives through a red light, it should not add to its own rule set that it should be able to drive through a red light. The context of the rule breaking situation, in this case it is an emergency vehicle that drove through the red light and not other vehicles, is an important factor in deciding whether to augment the given rule set based on observations.

My system has trouble with the cases mentioned in Section 6.3.3, and it also has trouble with out of vocabulary explanations. The current rule-learning platform examines the sentiment of an explanation and then parses the explanation into the appropriate rule format. The goal is to take a human readable explanation in plain text, and parse that into an "if this then that" format rule. Usually, this relies on looking for symbolic causal terms in the explanation, like "because" or time-varying symbolic terms like "before" and "after." If these keywords are not found in the explanation, the system fails to construct a rule. Dealing with out-of-vocabulary explanations and complex actions will be examined in future work.



```
saw green
cone location [-1.29255795 -0.57215381]
car location (-1.2945041266837571, 0.0283543363057777248, 3.135890209223959)
time: 1553648647.29

saw red
cone location [-5.30397911 -1.80882075]
car location (-4.315279739843591, -1.5229740091121877, -1.2719784897751123)
time: 1553648658.4

ERROR red appeared after green

saw green
cone location [-9.03512466 -0.67572284]
car location (-8.748572781701807, -0.6094111618329722, 1.749058628932332)
time: 1553648677.85

saw green
cone location [-12.65703604  -1.26450313]
car location (-12.519212968115556, -0.7505525339034774, 2.873493684718304)
time: 1553648693.24

saw red
cone location [-16.22980824  -1.69140707]
car location (-16.166375263352524, -2.252114769659417, -3.017005983588666)
time: 1553648704.87

ERROR red appeared after green

saw green
cone location [-17.40449314   0.3219946 ]
car location (-17.3020084240128, -0.07774055761703395, 0.23554681486803236)
time: 1553648715.28

saw green
cone location [-23.41332496   0.51735908]
car location (-23.506701993509182, 0.6253202967230022, -2.4394913240858176)
time: 1553648746.08

saw red
cone location [-25.23062349  -1.62097142]
car location (-25.68256165692277, -1.4077589729910873, -2.076386515538853)
time: 1553648753.19

ERROR red appeared after green
```

Figure 6-4: The dynamic reasonableness monitoring architecture.

6.6 Ongoing Work

Currently, the experiment is setup in a series of steps, and it is not a “real-time” system. The goal is for the monitor to be constantly running along side the RACECAR (or other autonomous system) so that is learning and monitoring more effectively. This process is visualized in Figure 6-4. The grey arrows designated ongoing work in closing the loop for the rule leaning system to work dynamically with the monitoring system in real-time.

In the current iterations of this system, the explanations are generated separately, incorporated into the log, and then processed by the rule learning system. If a new rule is generated, then the rule list is augmented with the new rule, and the monitor is updated. In future iterations of the system, I will add explanations from the monitor to the rule learning system. The key idea is that the monitor is adaptable; not just to multiple applications, but also to multiple domains and situations. The behavior of the monitor (and all similar agents) should be flexible and self-aware; so that its own explanations can be used to justify similar actions in the future.

6.7 Contributions and Discussion

Driving is a complex task, and corner cases lack the large volume of training data necessary for models to make the correct decision based on input. Instead of exhausting all possibilities for driving corner cases, I propose that the autonomous system can evaluate a new situation using two components - commonsense and a set of driving rules - and then explain its decision based on this information. Analogous to how humans approach a new situation, the autonomous vehicle would make a decision using prior knowledge and applicable driving rules. Those driving rules can then be updated as the car witnesses new situations.

My system, implemented as a *dynamic* monitor around the self driving unit, checks vehicle data and decisions for expected validity and reasonableness. The decision is reasonable if follows the rules set and commonsense knowledge base for the autonomous system. Similarly to how biologists are able to classify newly discovered species using a set of taxonomy rules, the set of driving rules can be applied to unforeseen situations that the system has never encountered before and make inferences about what driving actions are reasonable. As the autonomous vehicle encounters new situations, the set of driving rules can be updated to reflect acceptable behavior and expected encounters in the driving world. I propose that the information gap created by the incompleteness of anomalous training data can be supplemented by commonsense along with a set of rules regarding appropriate behavior. It is based on the system in Chapter 4.

This chapter focuses on building and using the RACECAR platform to evaluate the performance of the reasonableness monitor in dynamic and new environments. This was an initial study and the work can be expanded to include a richer set of data used in decision making, such as vehicle position, cone position, vehicle speed, information from potential other vehicles around the autonomous vehicle. A far more expansive set of rules can also be applied to the car's behavior and observations. The set of rules should originate from a driving handbook, which details the literal rules set for the vehicles on the road. Additionally, given that autonomous vehicles interact with other vehicles and it would be interesting to apply the anomaly detection and adaptable monitoring system to an autonomous vehicle in the presence of other possibly non-autonomous vehicles.

Chapter 7

System-wide Anomaly Detection

"We'll show you that you can build a mind from many little parts, each mindless by itself..." [1]

– Marvin Minsky

A previously working mechanism can fail in two distinct ways. One way is a *local* failure, caused by an error that can be localized to a single subsystem or component. I discussed how to localize opaque subsystem errors in Chapter 4 and how to localize sensor errors in Chapter 5. The second way a mechanism can fail is due to a failed *communication* amongst subsystems, which was the root cause of the Uber self-driving vehicle accident[2] [134]. In this chapter, I present an organizational architecture: Anomaly Detection through Explanations (ADE), which enables internal communication amongst the subsystems of a complex machine. It is inspired by the structure of successful human organizations. As Herb Simon said, "communication is 'absolutely essential to organizations' " [208].

[1]The revelation of Marvin Minsky's connection with Jeffrey Epstein came at the pinnacle of my PhD research. Because of that association, I was conflicted about whether to include Minsky's words and his prior work. I believe that it is important to be intellectually honest: I acknowledge that this chapter is inspired by Minsky's research. My inclusion of Minsky's words does not imply my support for any of Epstein's behavior or that of his associates.

[2]When inconsistent judgements arise, an arbitrary subsystem is ignored: https://www.theinformation.com/articles/uber-finds-deadly-accident-likely-caused-by-software-set-to-ignore-objects-on-road

7.1 The Problem

Complex mechanisms have limited internal reasoning. In some cases, they have none; so they have no ability to reason. For self-driving vehicles, adversarial attacks using a few pieces of tape tricked a vision system into classifying a perceived a stop sign as a 45 mph sign [58]. Biased facial recognition algorithms[3] have been extended to pedestrian detection [237]. It is well known that the "best performing" AI algorithms are brittle, "deep learning" subsystems [170]. But when these algorithms are connected to self-driving applications or other mission-critical, safety-critical applications, these mistakes have *consequences*.

I created a system-wide architecture that facilitates *communication* amongst parts. The communication is a symbolic explanation. The key idea is that the explanation is for the *machine*[4]; the underlying explanations to reconcile inconsistencies amongst subsystems.

But how does the architecture decide for itself which subsystem or component is the most "correct" or "reasonable?" To deal with conflicting explanations, I built an explanation synthesizer; which examines the input explanations, and validates that the underlying reasons do not violate the high-level rules from a priority hierarchy. In this chapter, I demonstrate the ADE on a critical example: the Uber self-driving vehicle accident [180]. For quantitative analysis, I inserted failures in an existing self-driving vehicle data set [31]. My analysis in Section 7.4.5 shows that using ADE, with an explanation synthesizer results in more robust failure detection.

7.2 System Monitoring Architecture

The ADE architecture is composed of reasonableness monitors around each subsystem and a explanation synthesizer to reconcile inconsistencies amongst underlying

[3]Facial recognition systems misidentify people with darker skin tones 5-10 times more than lighter skin tones [86].

[4]In Chapter 4, I showed the output of a reasonableness monitor: a natural-language explanations for an end user. I mentioned that the explanations are also symbolic. This chapter contributes a novel use of symbolic, dynamic explanations for machine diagnosis.

subsystems. The ADE reasoning method detects failures and anomalies in three steps:

1. Generating qualitative descriptions for each committee or subsystem.
2. Monitoring the outputs of each committee or subsystem.
3. Detecting, reconciling, and explaining inconsistencies[5].

The ADE architecture in Figure 7-1 is a *simplified* model of a self-driving car[6]. It is the minimal architecture needed to (1) detect and explain the cause of the Uber self-driving accident (in Section 7.4.2) and to (2) diagnose the mistakes I inserted, in Section 7.4.4. The dotted borders around the subsystems are reasonableness monitors. The translucent red component is the actuation committee, which reports to the tactics monitor. The grey component is the explanation synthesizer, which monitors explanation outputs from the vision, LiDAR, and tactics subsystems.

There is a difference between a committee and a subsystem. A committee is a group of subsystems working together on a common task in the same language. For example, the tactics subsystem in Figure 7-1 contains the actuation *committee*. The actuation committee is composed of the braking, steering, and power *subsystems*. These subsystems work on the common task of moving and controlling the mechanics for driving a car. They communicate in the same CAN bus message language (from Section 3.1.1). For readability of the reasoning process, I refer to the actuation committee as the tactics subsystem.

7.2.1 Inspiration from Human Committee Structures

I have represented a complex system as a hierarchical model of introspective subsystems working together towards a common goal. This idea is inspired by human committee structures. In a human organization, tasks are distributed to committees

[5]If no inconsistencies are detected, then a summary is produced. The summary is a synthesized story of the underlying subsystem explanations.

[6]A comprehensive architecture may enable more effective reasoning in real-world environments.

of personnel[7]. Each committee is composed of personnel who work together to accomplish committee tasks. A person may be a member of several committees, thus providing communication about the *interaction* of tasks of those committees. However, a person may not know much about the work of a committee they are not a member of. In fact, the *technical language* of different kinds of tasks may not have much overlap.[8]

However, good committees are able to survive bad work by a member, because the other members of the committee observe each other's work and can jointly decide actions to be taken to correct bad work or to discipline or expel a misbehaving member. Such an organization, though less efficient than one where each task is assigned to an individual working independently, is more robust to failure and more secure. It is hard for a single member to undermine the mission.

Each committee has a supervisor that assigns the goals for the committee to work on and monitors their performance, making adjustments as necessary[9]. Of course, the supervisor may be faulty, so if the members of the committee observe that the supervisor is acting inappropriately, they, as a group, can complain to a supervisory committee that the faulty supervisor is a member of. Although not all successful organizations function this way, it is a necessary safeguard for machines that have safety-critical or mission critical tasks.

In this chapter, I applied the organization of a human committee to a complex system. Each subsystem is part of a committee: a reasonableness monitor which is consistently observing and checking the underlying subsystem's behavior. The "supervisor" is an explanation synthesizer, that sets high-level goals and priorities in the case of disagreements. If the synthesizer is faulty, then the priorities can be changed: individual priorities can be removed, discounted (reordered), and/or new priorities can be added[10]. The synthesizer is *dynamic*, and different synthesizer

[7]The machine equivalent is committees of parts or subsystems.

[8]Similarly, in complex systems, each committee is speaking a different language. For example, the tactics subsystem, composed of the actuation committee, is communicating in low-level sensor outputs, which the perception committee (composed of the vision system) is communicating in a symbolic language. I describe this problem in Section 7.2.2.

[9]In my architecture, the committee supervisor is the explanation synthesizer in Section 7.3.

[10]In future work, I may investigate how these priorities could be learned through the committee

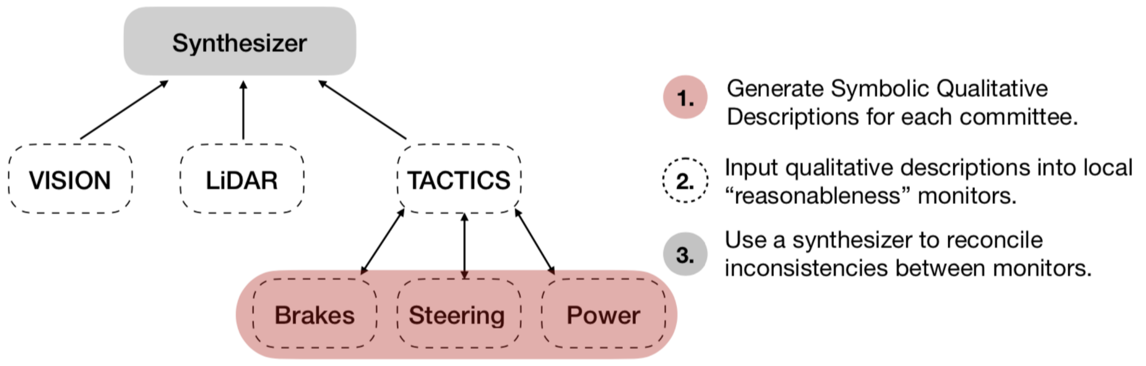

Synthesizer
VISION
LiDAR
TACTICS
Brakes
Steering
Power
1. Generate Symbolic Qualitative Descriptions for each committee.
2. Input qualitative descriptions into local "reasonableness" monitors.
3. Use a synthesizer to reconcile inconsistencies between monitors.

Figure 7-1: The ADE architecture model for a simplified self-driving vehicle. It is composed of reasonableness monitors (dotted borders) around each subsystem and explanation synthesizer

configurations yield different safeguards. I show the results of different configurations in Section 7.4.5.

I call this idea "committee-based anomaly detection with explanations." I show that using (1) a common symbolic explanation language (2) a system organization of introspective committees (reasonableness monitors applied to full subsystem design), results in a more robust system. The subsystems monitor each other's behavior, and disagreements amongst parts are identified with less ambiguity, since the *internal* communication is in a common language.

7.2.2 Generating Qualitative Descriptions

The outputs[11] of the parts of any complex machine vary in abstraction. For example, the labels output by an opaque vision processing systems in Chapter 4 are a mostly symbolic list of high-level concepts. The sensor subsystems, e.g., LiDAR or weather sensors, output a (possibly uninterpretable) log of data[12]. But to reconcile inconsistencies between subsystems, the subsystems need to argue amongst themselves. The arguments must be in the same language, otherwise vital reasons may be discounted

member's explanations.

[11]The outputs of a subsystem may be an action (e.g. a mechanical action like tightening a pinion) or a log (e.g. the readings of a tire pressure sensor over a time interval).

[12]These sensor output logs are typical of other "lower level" subsystems of the vehicle, like braking, steering, power control, etc. I explained how to interpret these basic outputs after-the-fact in Chapter 3. Another example is the "point cloud" output from the LiDAR subsystem in Chapter 5.

```
IF( AND('(?x) is moving'
    '(?x) isA animal',
    THEN('(?x) is reasonable.'))
```

Listing 8: A reasonableness rule for perception. If an object is perceived as moving and the object is an animal, then it is a reasonableness perception.

arbitrarily.

The subsystem's output is translated into a qualitative description. For the vision system, these are the output labels from the vision processing subsystem. For the LiDAR system, this is the sensor interpretation from Chapter 5, and for the tactics subsystem (which corresponds to the brakes, steering, and power control) it is the qualitative summary and analysis generated from the ex post facto explanation system from Chapter 3. A list of the qualitative descriptions from each subsystem are input into a reasonableness monitor [73]. Each monitor outputs for symbolic support and a justification of reasonableness. These justifications are the basis for each subsystem's argument.

7.2.3 Monitoring for Reasonableness within Each Subsystem

Recall from Chapter 4 that a reasonableness monitor is a sanity check for the outputs of a subsystem. The list of qualitative descriptions forward-chained with commonsense rules to extract more data. Each subsystem has its own set of commonsense rules. For lower-level components (e.g., the tactics subsystem) these are safe-driving rules. For example, if a vehicle is traveling at a high speed, then the vehicle should not make a sudden stop. Other safe-driving rules implement a qualitative physics idea: if the vehicle slows down and changes direction slowly, then the resulting turn is safe[13].

After forward-chaining, the monitor checks the data against a set of reasonableness rules. Similarly to commonsense, each subsystem has its own set of reasonableness rules. The monitor outputs a judgement and justification of whether the input description is reasonable or not. An input is deemed "unreasonable" if there is no data

[13]This is defined precisely in first-order logic.

to support a reasonable claim, i.e., no data fires a rule that leads to a “reasonable” consequent. An example of a reasonableness rule for perception is in Listing 8.

Note that an unreasonable judgement does not necessarily indicate that a subsystem should be completely ignored. An unreasonableness judgement indicates that the subsystem’s output should be discounted in future decisions. For example, in the Uber self-driving car accident, which is described in Section 7.4.2, the vision processing subsystem perceived several different objects where the pedestrian was located: a bicycle, a vehicle, and an unknown object. The vision subsystem is acting unreasonably, it is not possible to perceive three different objects in the same location. The vision system outputs should be discounted, but not completely disregarded. The vision system is not corrupted, it’s confused. The *detection* of an object in that place is reasonable and correct, and the detection is used in the explanation synthesizer as evidence. The technical details of this reasoning is in Section 7.4.3.

7.2.4 Reconcile Inconsistencies with a Synthesizer

If there are conflicts between explanations, the explanation synthesizer decides which subsystem to trust or discount. The synthesizer uses a priority hierarchy, which indicates, in order, which priorities are the most important. If any of those priorities are violated, then that subsystem should be examined and its output should be discounted for in future decisions.

7.3 Explanation Synthesizer

The explanation synthesizer is an explanation compiler. It processes the explanations from its underlying parts, and synthesizes (or summarizes) the explanations. If there are conflicting explanations, the synthesizer constructs an argument tree. The argument tree contains all the reasons that need to be tested to validate each priority. The argument tree is dynamic. If more information is available, it can be added. If data is deemed invalid, that data can be removed. Since the arguments are a tree, the synthesizer can also be queried for counterfactual support. This may useful in an adversarial proceeding, which is discussed in Chapter 8.

7.3.1 Priority Hierarchy

Erroneous driving is prevalent in human and autonomously operated vehicles. Perhaps the operator glides through a stop sign (even though that conflicts with a driving rule) since no one is around. The behavior does not have consequences, and it is supported by a reasonable explanation, "since no one was around, the operator proceeded through a stop sign, even though the operator should have stopped due to the stop-sign rule." Since there are no consequences, this erratic behavior should not be classified as a failure[14].

However, some errors can cause system failures. For example, if the vehicle operator cannot identify a large object in the road, it should stop regardless. Large objects, especially ones that are moving, are threats to the vehicle and the people inside. Whereas smaller unidentified objects are not usually harmful to the vehicle. For example, moving transparent objects, like plastic bags, should be ignored. But small sharp objects, like nails, or potholes and uneven paving can can flat tires, leading to accidents and passenger discomfort. Most autonomous vehicles struggle with this sort of reasoning, causing consistent starting and stopping behavior[15].

I created a priority hierarchy to apply high-level safety constraints in self-driving. The priorities are as follows (in order):

1. Passenger Safety

2. Passenger Perceived Safety

3. Passenger Comfort

4. Efficiency (e.g. Route efficiency)

[14]Of course, this behavior should be recorded to avoid a repeated error in a critical environment.

[15]"Herky jerky" or constant starting and stopping has become an "Achilles heal" for self-driving: `https://www.wired.com/story/ride-general-motors-self-driving-car/`. This discomfort lead many vehicle manufacturers to explicitly ignore objects detected with low confidence scores, instead of trying to reason about which objects are threats (or not).

A passenger is safe if:
The vehicle proceeds at the same speed and direction, AND
The vehicle avoids threatening objects.

Figure 7-2: The conditions for passenger safety as a natural language abstract goal.

In this chapter, I specifically focus on the first priority: passenger safety[16]. Passenger safety can be expressed as an abstract goal in Figure 7-2. It requires two conditions: the vehicle needs to be proceeding "safely": there does not exist any sudden changes in vehicle speed or direction. The other condition is that there are no *threats*: large moving objects close to the vehicle. The major cause of failures in autonomous driving have been due to violating these two constraints [151].

7.3.2 Underlying Logic Language

Let's focus on the high level goal for the first priority: passenger safety, in Figure 7-2. This goal can be strongly defined in first-order logic. Let s and t be successive states, and let v be a qualitative description of the vehicle's velocity. Then Equation 7.1 defines the sufficient conditions for passenger safety.

$$\begin{aligned} (\forall s,t \in STATE, v \in VELOCITY \\ ((self, moving, v), \text{state}, s)\wedge \\ (t, \text{isSuccesorState}, s)\wedge \\ ((self, moving, v), \text{state}, t)\wedge \\ (\nexists x \in OBJECTS \text{ s.t.} \\ ((x, isA, threat), \text{state}, s)\vee \\ ((x, isA, threat), \text{state}, t))) \\ \Rightarrow \text{(passenger, hasProperty, safe)} \end{aligned} \tag{7.1}$$

As long as the vehicle is moving at the same speed, and there are no threatening

[16] I worked on a short technical report about different metrics of efficiency. I co-authored a short article on different navigation "efficienty" metrics: `https://aipulse.org/mob-ly-app-makes-driving-safer-by-changing-how-drivers-navigate/`

```
IF ( AND('moving (?v) at state (?y)', '(?z) succeeds (?y)',
         'moving (?v) at state (?z)'),
     THEN('safe driving at velocity (?v) during (?y) and (?z)'))
```

Listing 9: The safe transition rule in implementation. The variables `?v,?y,?z` correspond to the vehicle velocity, starting state and successor state.

objects in the way of the vehicle, then the passenger is safe (and satisfying the first rule in the priority hierarchy). However, it is left to define "a threat". This is also defined in first-order logic. Let s be a state, and let x be an object and v be a velocity in Equation 7.2.

$$\begin{aligned}(\forall s \in STATE, x \in OBJECT, v \in VELOCITY\\ ((x, moving, v), \text{state}, s)\wedge\\ ((x, locatedNear, self), \text{state}, s)\wedge\\ ((x, isA, large\_object), \text{state}, s)\\ \Leftrightarrow ((x, isA, threat), \text{state}, s))\end{aligned} \tag{7.2}$$

7.3.3 Abstract Rules

In the implementation, I use the logic in Equation 7.1 and Equation 7.2 to define rules in python. For example, the safe transition rule is defined in Listing 9. Notice that the rule is abstract and contains placeholders for the velocity and states: `(?v)`, `(?y)`, `(?z)` respectively.

The rules form the simplified natural language goal tree in Listing 10, and the AND-OR tree in Listing 11. The goal tree is generated by backward-changing the list of rules to a specified goal, which is specified for each priority. The goal for passenger safety is: `passenger is safe at velocity V between s and t` where `V, s`, and `t` are given by the data, and `obj` corresponds to all the objects encountered between s and t. The implementation is in the Appendix in Listing 18.

```
passenger is safe,
    AND(
        safe transitions,
        NOT(threatening objects)
```

Listing 10: The high-level goal tree for passenger safety. It ensures that the the vehicle avoids threatening objects (large, moving objects located close to the vehicle) and it makes smooth transitions (there is not a large or sudden qualitative change between two successive state).

```
passenger is safe at velocity V between s and t
    AND( AND( moving V at state s
            t succeeds s
            moving V at state t )
         AND(
            OR  (  obj is not moving at s
                   obj is not locatedNear at s
                   obj is not a large object at s)
            OR  (  obj is not moving at t
                   obj is not locatedNear at t
                   obj is not a large object at t ) ) )
```

Listing 11: The implemented goal tree used for passenger safety in the explanation synthesizer. 'safe transitions' and 'threatening objects' have been expanded, as defined in Equation 7.1 and Equation 7.2.

```
passenger perceived safe,
    AND(
        cautious transitions,
        NOT(ominous objects) )
```

Listing 12: The high-level natural language goals for passenger perceived safety.

The other abstract rules for the other properties are not used in this implementation. The focus of this work is to detect failures that can cause harm, and the first priority is sufficient to ensure that. But for sake of example, the natural language abstract goal tree for perceived safety is in Listing 12. Note it is assumed that the first priority has been met for all transitions. So that this priority checks for different behaviors: cautious transitions (which is defined as avoiding reckless driving) and not avoiding ominous objects[17].

7.4 Evaluation

In order to evaluate ADE, I relied on two studies. My colleagues and I simulated the Uber accident and generated a log that was similar to the accident data from their report [80, 180]. I validated that the algorithm (1) detected the inconsistency and (2) could explain the inconsistency and why it is critical (in terms of the given priority hierarchy). I also wanted to ensure that the explanation was "similar" to the to the Uber accident testimony; that the explanation was true to the failure explained in the Uber report. The second evaluation is a quantitative study to detect and explain simulated failures. To my knowledge, this is the first data set of multimodal failures in the self-driving vehicle domain[18].

[17]This was not explored. But an ominous object may be something with a big shadow: some illusion that appears larger than it actually appears.

[18]A self-driving vehicle has multimodal interaction (multiple modes of interaction) with an operator: haptic feedback, video, etc.

7.4.1 Simulation Setup

The simulation modeled the events of the Uber Accident Scenario described in detail below. This simulation was performed using CARLA, an open-source simulator for self-driving research [56]. The primary data recorded in this simulation included raw images, semantic-segmented images, and LiDAR point clouds.

The simulation was performed on a machine running Ubuntu 18.04 LTS. The version of CARLA running on the machine at the time of testing was 0.9.6. In addition, CARLA renders the simulation using Unreal Engine, which has was installed separately. I used Unreal Engine version 4.22 for testing.

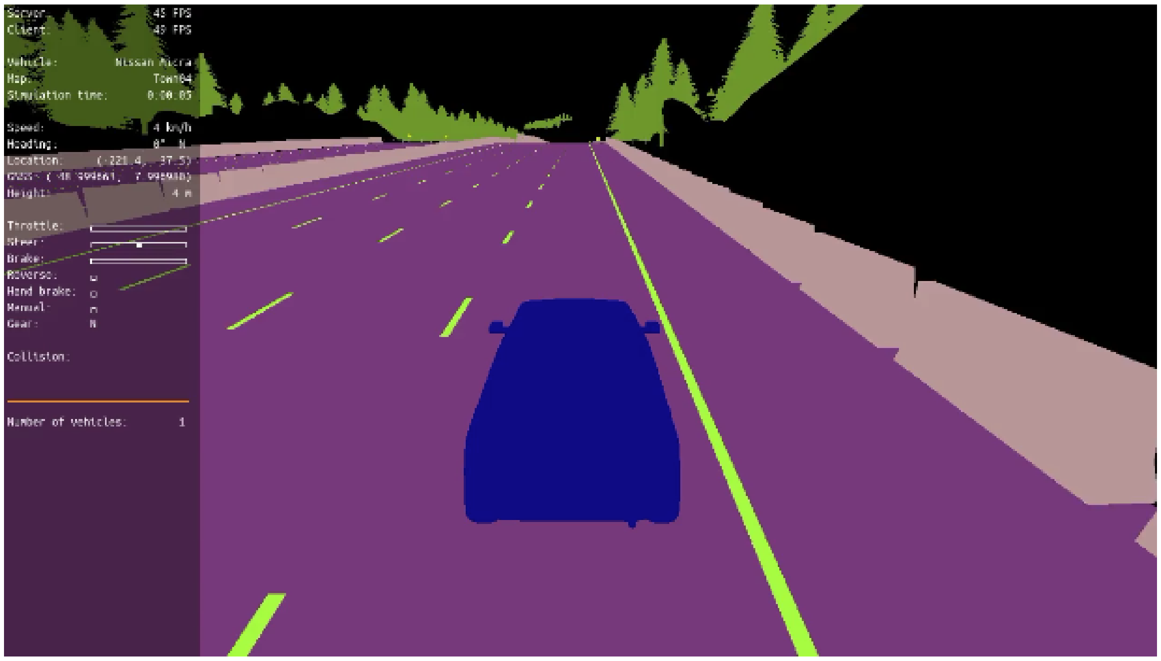
7.4.2 Uber Accident Scenario

On March 18, 2018, the first reported self-driving pedestrian fatality occurred. The vehicle was an Uber Technologies, Inc. test vehicle: a modified 2017 Volvo XC90 with a self-driving system in computer control mode. At approximately 9:58 p.m that evening, the vehicle struck a pedestrian on northbound Mill Avenue, in Tempe, Maricopa County, Arizona. Although the test vehicle had a human safety driver, the driver was not paying attention at the moments before impact. The following is from the Uber accident preliminary report.

> "According to data obtained from the self-driving system, the system first registered radar and LiDAR observations of the pedestrian about 6 seconds before impact, when the vehicle was traveling at 43 mph. As the vehicle and pedestrian paths converged, the self-driving system software classified the pedestrian as an unknown object, as a vehicle, and then as a bicycle with varying expectations of future travel path. At 1.3 seconds before impact, the self-driving system determined that an emergency braking maneuver was needed to mitigate a collision. According to Uber, emergency braking maneuvers are not enabled while the vehicle is under computer control, to reduce the potential for erratic vehicle behavior. The vehicle operator is relied on to intervene and take action. The system is

not designed to alert the operator" [180].

This is a motivating use case of the need for system-level communication. I generated this scenario in CARLA [56] and analyzed the logs after the fact. In the following sections, I demonstrate the ADE process on that simulated log.



```
Server:                   45 FPS
Client:                   49 FPS

Vehicle:             Nissan Micra
Map:                       Town04
Simulation time:          0:00:05

Speed:                     4 km/h
Heading:                    0°  N
Location:         (-221.4,  37.5)
GNSS: ( 48.999861,   7.999940)
Height:                       4 m

Throttle:
Steer:
Brake:
Reverse:
Hand brake:
Manual:
Gear:        N

Collision:

Number of vehicles:             1
```

Figure 7-3: A screenshot of the Uber accident simulation (in segmentation mode) on the Carla Platform.

Generating Qualitative Descriptions

From the Uber accident data analysis, the "vehicle was traveling at 43 mph" and "the self-driving system software classified the pedestrian as an unknown object, as a vehicle, and then as a bicycle with varying expectations of future travel path, " and for the sensor information LiDAR had detected the pedestrian "...about 6 seconds before impact" [180].

Note, that due to limitations in Carla, it was not possible to simulate a pedestrian walking with a bicycle. Therefore, for the LiDAR data, I manually added noise and to make the detection range reflect the length of the bicycle. Besides that augmentation, the raw data is processing automatically with edge detection (from Chapter 3) and

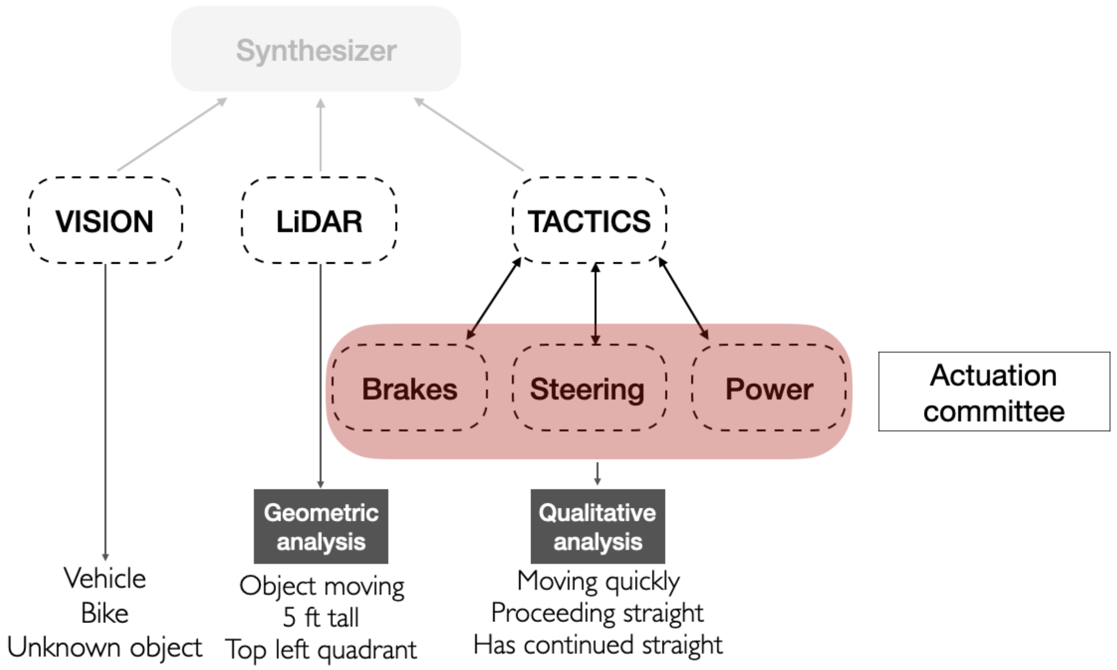


Figure 7-4: The qualitative description outputs from my simulation of the Uber accident in the ADE architecture.

sensor interpretation (from Chapter 5). Since the vision system outputs symbolic concepts, I represented the outputs of the vision system as oscillating among: vehicle, bike, and an unknown object. This is shown in a diagram of the ADE architecture in Figure 7-4.

Monitoring

Each qualitative description is input into reasonableness monitor. The monitored outputs are as follows (in human readable form):

1. VISION: This vision perception is unreasonable. There is no commonsense data supporting the similarity between a vehicle, bike and unknown object except that they can be located at the same location. This component's output should be discounted.

2. LIDAR: This lidar perception is reasonable. An object moving of this size is a large moving object that should be avoided.

3. TACTICS: This system state is reasonable given that the vehicle has been moving quickly and proceeding straight for the last 10 second history.

Note, that these are also represented in symbolic triples to be used by the synthesizer. The triples are stored in a pandas table so they are also indexed[19].

Synthesizing

The explanations are symbolic. Below are a few highlights of these reasons (the ones that are deemed "important" for the synthesizer).

1. VISION:

```
(monitor, judgement, unreasonable)
(input, isType, labels)
(all_labels, inconsistent, negRel)
(all_labels, notProperty, nearMiss)
(all_labels, locatedAt, consistent)
(monitor, recommend, discount)
```

2. LIDAR:

```
(monitor, judgement, reasonable)
(input, isType, sensor)
(input_data[4], hasSize, large)
(input_data[4], IsA, large_object)
(input_data[4], moving, True)
(input_data[4], hasProperty, avoid)
(monitor, recommend, avoid)
```

Note: `input_data[4]` corresponds to the detection of the pedestrian with the bicycle. There were other, smaller objects detected that were not deemed `threats`.

[19]Indexing is essential, so that the triples can refer to other triples. Although, the latest version of RDF, published in 2014, allows for RDF Quads `https://www.w3.org/TR/2014/REC-rdf11-concepts-20140225/`.

3. TACTICS:

```
(monitor, judgement, reasonable)
(input, isType, history)
(input_data, moving, True)
(input_data, direction, forward)
(input_data, speed, fast)
(input_data, consistent, True)
(monitor, recommend, proceed)
```

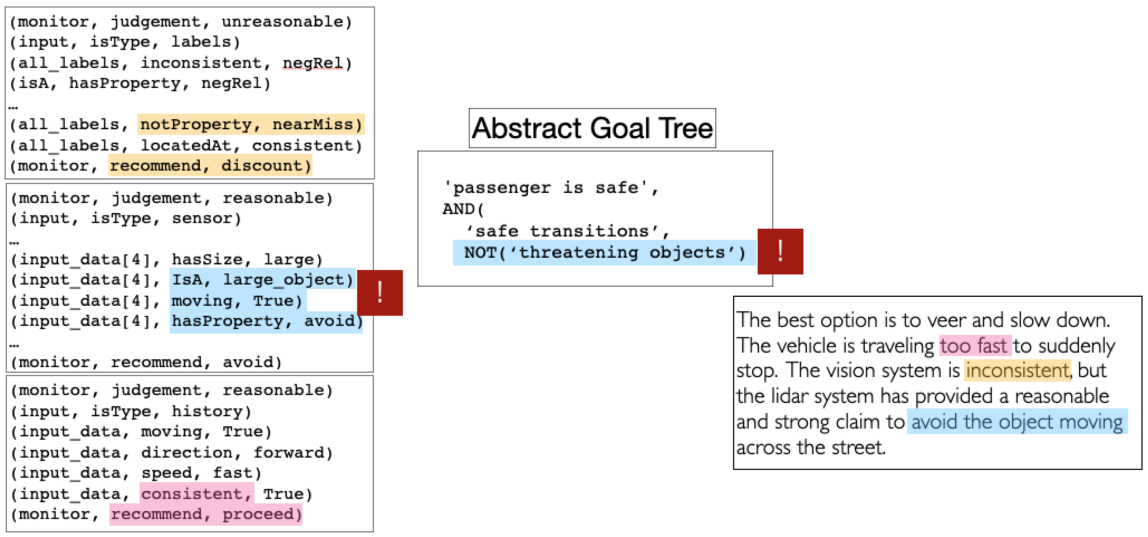
These symbolic reasons are passed to the explanation synthesizer, which finds that the LiDAR's data, specifically, the object described in `input_data[4]`, violates the goal: `NOT ('threatening objects')`. The final output, is the follow explanation, in human readable form:

```
The best option is to veer and slow down.
The vehicle is traveling too fast to suddenly stop.
The vision system is inconsistent, but the LiDAR system
has provided a reasonable and strong claim to avoid the object
moving across the street.
```

This is shown graphically in Figure 7-5, where the corresponding reasons are highlighted in the final judgment and explanation.

7.4.3 Reasoning

How does the synthesizer reason about threatening objects? We see that the LiDAR detection: `input_data[4]` is a threat. But how does the synthesizer know that? The synthesizer checks if the goal tree is satisfied. But a statement is not met: `OR ( obj is not moving at s, obj is not locatedNear at s, obj is not a large object at s)` from Listing 11 is not satisfied. This fires the threat rule. Now the synthesizer has added new data: `(input_data[4], IsA, threat)`. This new piece of data is



```
(monitor, judgement, unreasonable)
(input, isType, labels)
(all_labels, inconsistent, negRel)
(isA, hasProperty, negRel)
…
(all_labels, notProperty, nearMiss)
(all_labels, locatedAt, consistent)
(monitor, recommend, discount)
```

```
(monitor, judgement, reasonable)
(input, isType, sensor)
…
(input_data[4], hasSize, large)
(input_data[4], IsA, large_object)
(input_data[4], moving, True)
(input_data[4], hasProperty, avoid)
…
(monitor, recommend, avoid)
```

```
(monitor, judgement, reasonable)
(input, isType, history)
(input_data, moving, True)
(input_data, direction, forward)
(input_data, speed, fast)
(input_data, consistent, True)
(monitor, recommend, proceed)
```

Abstract Goal Tree

```
'passenger is safe',
AND(
  'safe transitions',
  NOT('threatening objects')
```

The best option is to veer and slow down. The vehicle is traveling too fast to suddenly stop. The vision system is inconsistent, but the lidar system has provided a reasonable and strong claim to avoid the object moving across the street.

Figure 7-5: The symbolic reasons that are used in the explanation synthesizer.

a "strong" reason. It is the argument in the synthesizer's explanation to trust the LiDAR subsystem and discount the vision subsystem.

7.4.4 Adding Mistakes to Existing Data

Self-driving data sets [31, 110, 69] do not contain errors that could lead to failures. They are hand-curated, so that the labelings and bounding boxes are error-free. The vehicle tactics operation is also smooth, so that there are not egregious mistakes in driving behavior. Since the data sets themselves do not have failures to explain, I added failures[20]. I scrambled labels and added noise. I hypothesized that the ADE architecture's explanation synthesizer would (1) more robustly identify a failure (2) explain which subsystem failed and why.

To valdiate my hypothesis, I added mistakes to the NuScenes data set [31]. NuScenes data was collected in various conditions, including dense traffic and challenging driving scenarios[21]. It also has a more complete 360 view camera, rather than

[20]In Section 1.1, I described an error as a technical property, and a failure as an error with consequences. While I cannot add "true" failures because the data set is already curated (i.e. the mistakes I add do not have consequences), I refer to these as failure since if the mistakes were occurred in an existing self-driving vehicle, they could cause system failures.

[21]NuScenes data was collected in Boston and Singapore; two very difficult (and different) driving environments).

the front facing camera data on KITTI [69]. NuScenes has 1000 different scenes (20 clips of driving) where each scene is split into frames (I refer to frames as *snapshots*). I define two types of mistakes: a frame error (a single point in time where obstacles are incorrectly labeled) and a scene error (a prolonged error over several frames).

I invoked errors at the frame level. For each frame, 50% of the objects in that frame are scrambled. This is performed randomly: when a frame is loaded, a `scrambleFlag` vector is randomized with 1's and 0's; corresponding to whether the object in question should be "scrambled" or not. I invoked two types of errors:

1. Label Errors: The "true" object label is replaced with another label.

2. "Noise" Errors: The object size is perturbed.

Label errors are chosen at random and retain the same label distribution on the data set. Noise errors are also chosen at random, but require careful manipulation. Naively adding random numbers to the object size clearly results in an error. For example, a car that is over 20 meters wide is clearly wrong. So instead, I added random noise from the range $[0, 2\sigma]$, where σ is the standard deviation of the object size in meters. Therefore I generate a set of noisy sizes, which are not "clearly wrong," but near misses [238].

A series of experiments are in Table 7.1. The table has three different configurations of the explanation synthesizer: no synthesizer (baseline), a naive preference (choosing one component over the other), and the "safety" priority explained in Section 7.3.1. The accuracy and analysis is shown in Table 7.1. This table contains the average of 10 randomized runs on the 18,538 annotations (objects detected) in the NuScenes mini data set.

7.4.5 Evaluation of Inserted Errors

Synthesizing increases correctness of accuracy of detecting errors. Note that the method is susceptible to false positives and negatives. Since I add noise in a reasonable range, i.e., $[0, 2\sigma]$, to scramble the data, it is difficult to separate errors from noise. If instead, I added noise that is significantly greater than 2σ, then the number of false positives and false negatives approaches zero, since the subsystem explanation *clearly* identifies a local error, and the synthesizer can confidently determine which system to discount.

Priority	Correctness	False Positives	False Negatives
No synthesizer	85.6%	7.1%	7.3%
Single subsystem	88.9%	7.9%	3.2%
Safety	93.5%	4.8%	1.7%

Table 7.1: A comparison of the ADE results on different synthesizer constraints. The "no synthesizer" option signifies that all subsystem errors are reported. The "single subystem" option means that one subsystem is arbitrarily chosen to always be given preference. The "safety" constraint is our default, where "threatening" objects are given a higher priority (to be classified as erroneous.)

Example explanations are in Table 7.2 of the object detected in Figure 7-6. I created an error by scrambling the label of a pedestrian to a "traffic cone." In the case that no errors are detected, the synthesizer outputs a summary. I focused on inserting frame (i.e, snapshot) errors because generating scene errors (i.e., video) requires careful tracking of objects, which is out of the scope of this thesis.

Examples

The scene monitor uses the explanation synthesizer to summarize the findings.

```
This scene with with 225 distinct annotations 2018-07-23
23:29:06.797517 is reasonable.  Explanation synthesized: Reasonable
scene with a car proceeding forward, turning left, and following a
van.  Perceived a parked truck, construction, and intersection.
```

This explanation can be compared with the description from the data set; where parked truck, construction and intersection are part of the scene description (amongst a few other concepts).

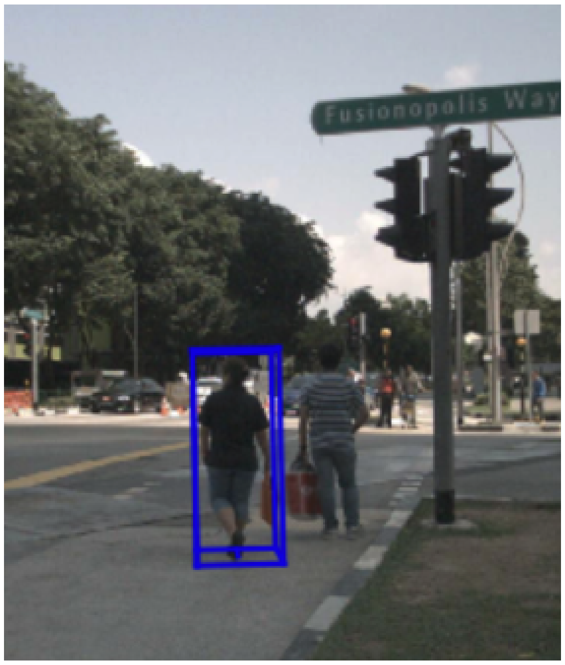


Figure 7-6: The “true” annotation of a pedestrian.

Regular Output	**Scrambled Output**
This sample’s 69 labeled objects are reasonable. Sample explanations: The human.pedestrian.adult located at [373.256, 1130.419, 0.8] is approximately the right size. It is somewhat close, located to the right.	At least one of this sample’s 69 labeled objects are unreasonable. Unreasonable explanations: The movable_object.trafficcone located at [373.256, 1130.419, 0.8] is not a reasonable size: it is too tall. There is no commonsense supporting this judgement. Ignoring objects detected to the right.
The vehicle.car located at is [353.794, 1132.355, 0.602] is approximately the right size. It is somewhat close, located to the right, past the movable_object.	The human.pedestrian.adult located at is [353.794, 1132.355, 0.602] is not a reasonable size: it is too wide and it is too deep. It’s location is too far away to be close to a street. Ignoring objects detected to the right.

Table 7.2: A comparison of the ADE system on regular and scrambled outputs. The regular output is a *summary* supporting that the judgement or action is reasonable. The scrambled output (where a different label than the true label is used) shows that the architecture can correctly identify judgements or actions that are incorrect.

7.5 Challenges and Benchmarks

There are threeways to evaluate the ADE architecture:

1. Detection: Generate logs from scenarios to detect failures.

2. Invoke errors: Scrambling multiple labels on existing data sets.

3. Real errors: Examining errors on the validation dataset of NuScenes leaderboard.

I validated the first detection task by simulating the Uber Carla scenario and explaining it. I discussed preliminary results for inserting errors in Section 7.4.4. The second validation is to examine the outputs of existing algorithms that are trained on some of these self-driving data sets. I wanted to find common failure scenarios by finding where existing algorithms failed. NuScenes [31] has several different online challenges including detection, tracking, and prediction. The testing sets of these challenges are private. I researched if I could acquire any of the top-performing algorithms and examine their validation errors. Unfortunately, most of these algorithms are not open source. Secondly, even if the source code was available, the source code requires significant changes to be applied to nuScenes[22]. While I was able to find many pre-trained models, I was not able to find one for the nuScenes challenges. This may be examined again in future work.

Other anomaly detection data sets are not applicable to my method. These data sets are are single modal: they contain outputs from a single subsystem with a consistent data distribution. The key contribution of ADE is that it examines *multiple* subsystems to make a judgement. These types of multimodal, anomalous data sets do not currently exist.

[22]Most of these algorithms are pre-trained on KITTI [69], the predecessor to nuScenes.

7.5.1 Other Potential Evaluations

Other evaluations could be performed in simulation. There are a number of challenge scenarios proposed[23] that have not been simulated or released. I am currently working on a set of challenge problems for anticipatory thinking in autonomous driving[24]. The goal is to develop scenarios that that require abstract, high-level anticipatory thinking [7], similar to the type of reasoning that humans do in difficult situations.

In other domains, I argue that explaining errors should be evaluated on *tasks* instead of data. Unlike other explanatory methods that are evaluated for end-users [76], my explanations for the *machine*. In future work, I will design tasks that require machine explanations to complete tasks. This is discussed in the Conclusion in Section 9.3.

7.6 Requirements to Apply ADE

Recall that ADE is an architecture and a reasoning process. The ADE architecture is application-dependent. The hierarchical model needs to be defined for each application. This requires constructing reasonableness monitors for each component (specifications in Section 4.5), and composing components into committees. In this Chapter, I showed *one* synthesizer that reconciles outputs from three committees. My methodology can also be applied to multiple committees with multiple synthesizers.

The explanation synthesizer, can be utilized without or without an underlying architecture definition. The explanation synthesizer has its own set of requirements.

1. Multiple pieces of information (e.g. vision, LiDAR, vehicle state) about corresponding things[25].

2. Priorities (e.g. safety) and associated rules.

[23]Carla challenges: `https://carlachallenge.org/challenge/nhtsa/`

[24]AAAI Fall Symposium on Anticipatory Thinking: `https://www.anticipatorythinking.ai`.

[25]The multiple pieces of information should overlap. If there is no overlapping information between the monitored parts, then the explanation synthesizer cannot *synthesize anything*; it will simply summarize disparate information. Test cases of this behavior are shown in Appendix B.4

Note that the explanation synthesizer can be utilized without the architecture, as long as it is provided with multiple explanations or justifications, and a priority hierarchy.

7.7 Related Work

The main goal of this work is to use *internal subsystem explanations* to decrease the number of false positives in anomaly detection. Anomaly detection is a data science and machine learning discipline [37]. Although, anomaly detection is also used in security to combat intrusion detection in networks [68]. Real-time anomaly detection requires scoring algorithms to dynamically detect “anomalous” streaming data, including a series of benchmarks [129]. The goal of anomaly detection is to be accurate, and reduce the number of false-positives and false-negatives. Some tactics include smoothing the output [85], or piece-wise approximations [229].

The final goal of this work is to provide interpretable explanations. Within the context of self-driving car, previous work has used reasoning systems, propagation [184], and models of expected vehicle physics and electromechanical behavior to create causal chains that explain the events leading up to and in an accident [75]. This work is also being extended to include commonsense rules of vehicle actions, so that it could monitor planning systems for inconsistent tactics.

My approach and position is similar to that proposed in Explainable Agency [128]. This refers to the ability of autonomous agents to explain their decisions and be questioned. Although I adhere to many of the principles of explainable agency, my goal is to extend these principles to *full system design*.

7.8 Limitations

ADE decomposes a complex machine into introspective committees or subsystems. This requires knowledge of the underlying complex machine structure. For the self-driving domain, I simplified a self-driving car into the three committees (vision, Li-

DAR, tactics) that are essential for planning. I also choose these committees since they are well-represented in self-driving vehicle data [31]. A similar architecture is applicable to other autonomous robotic systems like home robotics (without LiDAR), and autonomous flight (with additional sensor information and Radar).

Priorities have to be manually set. For self-driving, this was straight-forward, as the priority is *safety* of the passenger inside the vehicle. I cases where there is a variety of external distractions and near-perfect information, it may be important to consider which outside factors to prioritize; which reduces to the trolley problem [16]. One interesting area of future work would be to investigate whether these priorities can be learned from experience. This requires a *human-in-the-loop* to provide proper feedback. I will explore the right ways to incorporate human preferences into ADE. This has implications for system debugging, but also for personalizing autonomy. Each passenger may have their own preferences and priorities. There may be other meaningful priorities besides passenger safety (i.e., passenger comfort, or limited interruptions, or a smooth route). I will explore whether these can be learned through user feedback in ongoing work.

7.9 Conclusion and Future Work

Complex machines have insufficient communication between parts. I showed how to use *dynamic* explanations along with a logic system to reason *between* the subsystems of a complex system. This enables allows better system-wide communication, even with limited information, uninterpretable information, or receiving conflicting information from the underlying subsystems. I have motivated this use case with a self-driving failure example. I showed a quantitative evaluation on a data set where I inserted errors.

This chapter motivates a new view of anomaly detection. A view in which failures and errors are not necessarily outliers, but inexplicable instances. When an explanation is inadequate or inappropriate, the underlying subsystem or process should be corrected or disabled. The novel idea is using symbolic explanations as an internal language. The explanations facilitate better communication. Better communications can yield better performance; failures and errors are explicitly, logged, debugged, and reconciled. This applies to complex systems that include humans.

As machines and humans share control of tasks, communication is necessary. This is important for debugging, so that humans can improve complex systems, but also for education, where complex could "improve" or teach humans. Imagine a system where human interventions are well-communicated. The explanation supports the intervention, and the explanation is used to improve the system. The machine is introspective: the machine reflects and reasons about its behavior. The machine is articulate: the machine explains and describes its behavior to other systems (including a human) and itself. For most definitions, the machine is *intelligent*. This chapter is a first step towards articulate machines that can coherently explain themselves and learn from their mistakes: machines that are self-aware problem solvers.

Chapter 8

Philosophy of Explanations: A Review with Recommendations

"The word explanation occurs so continuously and has so important a place in philosophy, that a little time spent in fixing the meaning of it will be profitably employed."[1]

– J.S. Mill

During my PhD, there was a surge of work in explanatory artificial intelligence (XAI). This research area tackles the important problem that complex machines and algorithms often cannot provide insights into their behavior and thought processes. XAI allows users and parts of the internal system to be more transparent, providing explanations of their decisions in some level of detail. These explanations are important to ensure algorithmic fairness, identify potential bias/problems in the training data, and to ensure that the algorithms perform as expected. However, explanations produced by these systems is neither standardized nor systematically assessed. In an effort to create best practices and identify open challenges, I describe foundational concepts of explainability and show how they can be used to classify existing literature. I discuss why current approaches to explanatory methods for deep neural networks are insufficient. An earlier version of this review is available on arXiv [77]

[1]This is the first quote in the Chapter 1 of Sylvain Bromberger's book on explanations [30].

and as a conference proceeding [76]. The ideas about the *ethical implications* of explainability were part of a workshop paper [81].

8.1 Background and Foundational Concepts

This section provides background information about the key concepts of interpretability and explanability, and elaborates and details the meaningful differences between them.

8.1.1 What is an Explanation?

Philosophical texts show much debate over what constitutes an explanation. Of particular interest is what makes an explanation "good enough" or what really defines an explanation. Sylvain Bromberger says that good explanation depends on the question. In Bromberger's set of essays [30], he discusses the nature of explanation, theory, and the foundations of linguistics. Although for my work, the most important and interesting work is on "why questions." In particular, when you can phrase what you want to know from an algorithm as a why question, there is a natural qualitative representation of when you have answered said question–when you can no longer keep asking why. There are two why-questions of interest; why and why-should. Similarly to the explainable planning literature, philosophers wonder about the why-shouldn't and why-should questions, which can give the kinds of explainability requirements society desires. The details of the societal requirement for explanations are in Section 8.6.

There is also discussion in philosophy about what makes the best explanation. Gilbert Harman says it is a type of abductive reasoning.

> "In general, there will be several hypotheses which might explain the evidence, so one must be able to reject all such alternative hypotheses before one is warranted in making the inference. Thus one infers, from the premise that a given hypothesis would provide a 'better' explanation for the evidence than would any other hypothesis, to the conclusion that the

given hypothesis is true." [91]

This is slightly different than Charles Pierce's definition of abduction[2], which is to infer a premise from a conclusion [177]. While Paul R. Thagard agrees that "inductive inference is inference to the best explanation" [221], he also suggests three new criteria to evaluate the "best" explanation: consilience (converging to a conclusion), simplicity, and analogy.

Interactive Explanations

I argue that a good explanation *is* interactive. The user or program should be able to ask for details, inquire for more information, and collaborate on tasks. I argue that these types of interactive, collaborative tasks are also appropriate for *evaluation*[3].

8.1.2 Interpretability vs. Completeness

I argue that an explanation can be evaluated in two ways: according to its *interpretability*, and according to its *completeness*.

The goal of *interpretability* is to describe the internals of a system in a way that is understandable to humans. The success of this goal is tied to the cognition, knowledge, and biases of the user: for a system to be interpretable, it must produce descriptions that are simple enough for a person to understand using a vocabulary that is meaningful to the user[4].

The goal of *completeness* is to describe the operation of a system in an accurate way. An explanation is more complete when it allows the behavior of the system to be anticipated in more situations. When explaining a self-contained computer program

[2]Pierce's classic example of "abduction" explains rain. If it is observed that the grass is wet, it probably rained. He states that rain is the best explanation for wet grass, especially in his native area of New England. But this is not the best explanation in a desert location, where the best explanation may be a the result of a sprinkler system (especially if the grass is wet but the pavement is not.)

[3]I describe how to develop these evaluations, by designing collaborative tasks (between a human and machine) that require explanations for success, in Section 9.3

[4]If there is no "simple" explanation that supports a decision, this could be worrisome, and possibly unethical. I describe this and other ethical implications of XAI systems in Section 8.6.

such as a deep neural network, a perfectly complete explanation can always be given by revealing all the mathematical operations and parameters in the system.

The challenge facing explainable AI is in creating explanations that are both complete and interpretable: it is difficult to achieve interpretability and completeness simultaneously. The most accurate explanations are not easily interpretable to people; and conversely the most interpretable descriptions often do not provide predictive power.

Herman notes that we should be wary of evaluating interpretable systems using merely human evaluations of interpretability, because human evaluations imply a strong and specific bias towards simpler descriptions [96]. He cautions that reliance on human evaluations can lead researchers to create *persuasive* systems rather than transparent systems. He presents the following ethical dilemmas that are a central concern when building interpretable systems:

1) When is it unethical to manipulate an explanation
to better persuade users?
2) How do we balance our concerns for transparency and
ethics with our desire for interpretability?

I believe that it is fundamentally unethical to present a simplified description of a complex system in order to increase trust. The explanation may be optimized to hide undesirable attributes of the system. Such explanations are inherently misleading, and may result in the user justifiably making dangerous or unfounded conclusions.

To avoid this trap, explanations should allow a *trade-off* between interpretability and completeness. Rather than providing only simple descriptions, systems should allow for descriptions with higher detail and completeness at the possible cost of interpretability. Explanation methods should not be evaluated on a single point on this trade-off, but according to how they behave on the curve from maximum interpretability to maximum completeness.

8.1.3 Explainability of Deep Networks

Explanations of the operation of deep networks have focused on either explaining the *processing* of the data by a network, or explaining the *representation* of data inside a network. An explanation of processing answers "Why does this particular input lead to that particular output?" and is analogous to explaining the execution trace of a program. An explanation about representation answers "What information does the network contain?" and can be compared to explaining the internal data structures of a program.

A third approach to interpretability is to create *explanation-producing* systems with architectures that are designed to simplify interpretation of their own behavior. Such architectures can be designed to make either their processing, representations, or other aspects of their operation easier for people to understand.

8.2 Review

Due to the growing number of sub-fields, as well as the policy and legal ramifications [83] of opaque systems, the volume of research in interpretability is quickly expanding. Since it is intractable to review all the papers in the space, I focus on explainable methods in deep neural architectures, and briefly highlight review papers from other sub-fields.

8.2.1 Explanations of Deep Network Processing

Deep networks derive their decisions using a large number of elementary operations. For example, ResNet [93], a popular architecture for image classification, incorporates about 5×10^7 learned parameters and executes about 10^{10} floating point operations to classify a single image. Thus the fundamental problem facing explanations of such processing is to find ways to reduce the complexity of all these operations. This can be done by either creating a *proxy model* which behaves similarly to the original model, but in a way that is easier to explain, or by creating a *salience map* to highlight a small portion of the computation which is most relevant.

Linear Proxy Models

LIME is a model-agnostic[5] proxy method [189]. With LIME, a black-box system is explained by probing behavior on perturbations of an input, and then that data is used to construct a local linear model that serves as a simplified proxy for the full model in the neighborhood of the input. The method can be used to identify regions of the input that are most influential for a decision across a variety of types of models and problem domains. Proxy models such as LIME are predictive: the proxy can be run and evaluated according to its faithfulness to the original system. Proxy models can also be measured according to their model complexity, for example, number of nonzero dimensions in a LIME model. Because the proxy model provides a quantifiable relationship between complexity and faithfulness, methods can be benchmarked against each other, making this approach attractive.

Decision Trees

Another appealing type of proxy model is the decision tree. Efforts to decompose neural networks into decision trees have recently extended work from the 1990s, which focused on shallow networks, to generalizing the process for deep neural networks. One such method is DeepRED [257], which demonstrates a way of extending the CRED [197] algorithm (designed for shallow networks) to arbitrarily many hidden layers. DeepRED utilizes several strategies to simplify its decision trees: it uses RxREN [15] to prune unnecessary input, and it applies algorithm C4.5 [195], a statistical method for creating a parsimonious decision tree. Although DeepRED is able to construct complete trees that are closely faithful to the original network, the generated trees can be quite large, and the implementation of the method takes substantial time and memory and is therefore limited in scalability.

Another decision tree method is ANN-DT [200] which uses sampling to create a decision tree: the key idea is to use sampling to expand training using a nearest

[5]Model-agnostic means that the method (in this case, LIME) can be applied to any model.

neighbor method.

Automatic-Rule Extraction

Automatic rule extraction is another well-studied approach for summarizing decisions. Andrews et al. [9] outlines existing rule extraction techniques, and provides a useful taxonomy of five dimensions of rule-extraction methods including their expressive power, translucency and the quality of rules. Another useful survey can be found in the master's thesis by Zilke [256].

Decompositional approaches work on the neuron-level to extract rules to mimic the behavior of individual units. The KT method [66] goes through each neuron, layer-by-layer and derives an if-then rule by finding a threshold. Similar to DeepRED, there is a merging step which creates rules in terms of the inputs rather than the outputs of the preceding layer. This is an exponential approach which is not feasible for deep neural networks. However, a similar approach proposed by Tsukimoto [227] achieves polynomial-time complexity, and may be more tractable. There has also been work on transforming neural network to fuzzy rules [21], by transforming each neuron into an approximate rule.

Pedagogical approaches aim to extract rules by directly mapping inputs to outputs rather than considering the inner workings of a neural network. These treat the network as a black box, and find trends and functions from the inputs to the outputs. Validity Interval Analysis is a type of sensitivity analysis to mimic neural network behavior [222]. This method finds stable intervals, where there is some correlation between the input and the predicted class. Another way to extract rules using sampling methods [102, 44]. Some of these sampling approaches only work on binary input [219] or use genetic algorithms to produce new training examples [89]. Other approaches aim to reverse engineer the neural network, notably, the RxREN algorithm, which is used in DeepRED[257].

Other notable rule-extraction techniques include the MofN algorithm [225], which tries to find rules that explain single neurons by clustering and ignoring insignificant neurons. Similarly, The FERNN [204] algorithm uses the C4.5 algorithm [195] and tries to identify the meaningful hidden neurons and inputs to a particular network.

Although rule-extraction techniques increase the transparency of neural networks, they may not be truly faithful to the model. With that, there are other methods that are focused on creating trust between the user and the model, even if the model is not "sophisticated."

Salience Mapping

The salience map approach is exemplified by occlusion procedure by Zeiler [246], where a network is repeatedly tested with portions of the input occluded to create a map showing which parts of the data actually have influence on the network output. When deep network parameters can be inspected directly, a salience map can be created more efficiently by directly computing the input gradient (Simonyan [209]). Since such derivatives can miss important aspects of the information that flows through a network, a number of other approaches have been designed to propagate quantities other than gradients through the network. Examples are LRP [17], DeepLIFT [207], CAM [254], Grad-CAM [203], Integrated gradients [217], and SmoothGrad [211]. Each technique strikes a balance between showing areas of high network activation, where neurons fire strongest, and areas of high network sensitivity, where changes would most affect the output. A comparison of some of these methods can be found in Ancona [8].

8.2.2 Explanations of Deep Network Representations

While the number of individual operations in a network is vast, deep networks are internally organized into a smaller number of subcomponents: for example, the billions of operations of ResNet are organized into about 100 layers, each computing between 64 and 2048 channels of information per pixel. The explanation of deep network representations aims to understand the role and structure of the data flowing through these bottlenecks. This work can be divided by the granularity examined: representations can be understood *by layer*, where all the information flowing through a layer is considered together, and *by unit*, where single neurons or single filter channels are considered individually, and *by vector*, where other vector directions in representation space are considered individually.

Role of Layers

Layers can be understood by testing their ability to help solve different problems from the problems the network was originally trained on. For example Razavian [185] found that the output of an internal layer of a network trained to classify images of objects in the ImageNet data set produced a feature vector that could be directly reused to solve a number of other difficult image processing problems including fine-grained classification of different species of birds, classification of scene images, attribute detection, and object localization. In each case, a simple model such as an SVM was able to directly apply the deep representation to the target problem, beating state-of-the-art performance without training a whole new deep network. This method of using a layer from one network to solve a new problem is called *transfer learning*, and it is of immense practical importance, allowing many new problems to be solved without developing new data sets and networks for each new problem. Yosinksi [245] described a framework for quantifying transfer learning capabilities in other contexts.

Role of Individual Units

The information within a layer can be further subdivided into individual neurons or individual convolutional filters. The role of such individual units can be understood qualitatively, by creating visualizations of the input patterns that maximize the response of a single unit, or quantitatively, by testing the ability of a unit to solve a transfer problem. Visualizations can be created by optimizing an input image using gradient descent [209], by sampling images that maximize activation [253], or by training a generative network to create such images [169]. Units can also be characterized quantitatively by testing their ability to solve a task. One example of a such a method is network dissection [19], which measures the ability of individual units solve a segmentation problem over a broad set of labeled visual concepts. By quantifying the ability of individual units to locate emergent concepts such as objects, parts, textures, and colors that are not explicit in the original training set, network dissection can be used characterize the kind of information represented by visual networks at each unit of a network.

A review of explanatory methods focused on understanding unit representations used by visual CNNs can be found in [247], which examines methods for visualization of CNN representations in intermediate network layers, diagnosis of these representations, disentanglement representation units, the creation of explainable models, and semantic middle-to-end learning via human-computer interaction.

Pruning of networks [64] has also been shown to be a step towards understanding the role of individual neurons in networks. In particular, large networks that train successfully contain small subnetworks with initializations conducive to optimization. This demonstrates that there exist training strategies that make it possible to solve the same problems with much smaller networks that may be more interpretable.

Role of Representation Vectors

Closely related to the approach of characterizing individual units is characterizing other directions in the representation vector space formed by linear combinations of individual units. Concept Activation Vectors (CAVs) [112] are a framework for interpretation of a neural net's representations by identifying and probing directions that align with human-interpretable concepts.

8.2.3 Explanation-Producing Systems

Several different approaches can be taken to create networks that are designed to be easier to explain: networks can be trained to use *explicit attention* as part of their architecture; they can be trained to learn *disentangled representations*; or they can be directly trained to create *generative explanations*.

Attention Networks

Attention-based networks learn functions that provide a weighting over inputs or internal features to steer the information visible to other parts of a network. Attention-based approaches have shown remarkable success in solving problems such as allowing natural language translation models to process words in an appropriate non-sequential order [230], and they have also been applied in domains such as fine-grained image classification [242] and visual question answering [145]. Although units that control attention are not trained for the purpose of creating human-readable explanations, they do directly reveal a map of which information passes through the network, which can serve as a form of explanation. Data sets of human attention have been created [46], [174]; these allow systems to be evaluated according to how closely and their internal attention resembles human attention.

While attention can be observed as a way of extracting explanations, another interesting approach is to train attention explicitly in order to create a network that has behavior that conforms to desired explanations. This is the technique proposed by Ross [192], where input sensitivity of a network is adjusted and measured in order to create networks that are "right for the right reasons"; the method can be used to steer the internal reasoning learned by a network. They also propose that the method can be used to learn a sequence of models that discover new ways to solve a problem that may not have been discovered by previous instances.

Disentangled Representations

Disentangled representations have individual dimensions that describe meaningful and independent factors of variation. The problem of separating latent factors is an old problem that has previously been attacked using a variety of techniques such as Principal Component Analysis [104], Independent Component Analysis [99], and Nonnegative Matrix Factorization [23]. Deep networks can be trained to explicitly learn disentangled representations. One approach that shows promise is Variational Autoencoding [115], which trains a network to optimize a model to match the input probability distribution according to information-theoretic measures. Beta-VAE [97] is a tuning of the method that has been observed to disentangle factors remarkably well. Another approach is InfoGAN [40], which trains generative adversarial networks with an objective that reduces entanglement between latent factors. Special loss functions have been suggested for encouraging feed-forward networks to also disentangle their units; this can be used to create interpretable CNNs that have individual units that detect coherent meaningful patches instead of difficult-to-interpret mixtures of patterns [249]. Disentangled units can enable the construction of graphs [248] and decision trees [250] to elucidate the reasoning of a network. Architectural alternatives such as capsule networks [194] can also organize the information in a network into pieces that disentangle and represent higher-level concepts.

Generated Explanations

Finally, deep networks can also be designed to generate their own human-understandable explanations as part of the explicit training of the system. Explanation generation has been demonstrated as part of systems for visual question answering [12] as well as in fine-grained image classification [95]. In addition to solving their primary task, these systems synthesize a "because" sentence that explains the decision in natural language. The generators for these explanations are trained on large data sets of human-written explanations, and they explain decisions using language that a person would use.

Multimodal explanations that incorporate both visual pointing and textual explanations can be generated; this is the approach taken in [174]. This system builds upon the winner of the 2016 VQA challenge [67], with several simplification and additions. In addition to the question answering task and the internal attention map, the system trains an additional long-form explanation generator together with a second attention map optimized as a visual pointing explanation. Both visual and textual explanations score well individually and together on evaluations of user trust and explanation quality. Interestingly, the generation of these highly readable explanations is conditioned on the output of the network: the explanations are generated based on the decision, after the decision of the network has already been made.

The rise of dialog systems and chatbots for customer care have lead to research in how to build trust between users and technology. The most straightforward methods eschew sophisticated natural language understanding techniques and mimic conversations to build trust [179] either by scripted conversation[6] or wizard-of-oz methods [109].

8.3 Related Work

This section contains a summary of review papers, and an overview of interpretability and explainability in other domains.

8.3.1 Interpretability

A previous survey attempted to define taxonomies and best practices for a "strong science" of interpretability [54]. The authors define interpretability as "the ability to explain or to present in understandable terms to a human" and suggest a variety of definitions for explainability, converging on the notion that interpretation is the act of discovering the evaluations of an explanation. The main contribution of the paper is a taxonomy of modes for interpretability evaluations: application-grounded, human-grounded, and functionally grounded. The authors state interpretability is required when a problem formulation is incomplete, when the optimization problem – the key definition to solve the majority of machine learning problems – is disconnected from evaluation. Since their problem statement is the incompleteness criteria of models, resulting in a disconnect between the user and the optimization problem, evaluation approaches are key.

The first evaluation approach is application-grounded, involving real humans on real tasks. This evaluation measures how well human-generated explanations can aid other humans in particular tasks, with explanation quality assessed in the true context

[6]Juergen Pirner, creator of the 2003 Loebner prize winner Jabberwock, has been outspoken about the scripting process behind a chatbot.

of the explanation's end tasks. For instance, a doctor should evaluate diagnosis systems in medicine. The second evaluation approach is human-grounded, using human evaluation metrics on simplified tasks. The key motivation is the difficulty of finding target communities for application testing. Human-grounded approaches may also be used when specific end-goals, such as identifying errors in safety-critical tasks, are not possible to realize fully. The final evaluation metric is functionally grounded evaluation, without human subjects. In this experimental setup, proxy or simplified tasks are used to prove some formal definition of interpretability. The authors acknowledge that choosing which proxy to use is a challenge inherent to this approach. There lies a delicate trade-off between choosing an interpretable model and a less interpretable proxy method which is more representative of model behavior; the authors acknowledge this point and briefly mention decision trees as a highly interpretable model. In my XAI taxonomy, Table 8.1, decision trees and proxy models explain the same part of an underlying model (namely, the model's *processing*).

8.3.2 Explainable AI for HCI

One previous review paper of explainable AI performed a sizable data-driven literature analysis of explainable systems [1]. In this work, the authors move beyond the classical AI interpretability argument, focusing instead on how to create practical systems with efficacy for real users. The authors motivate AI systems that are "explainable by design" and present their findings with three contributions: a data-driven network analysis of 289 core papers and 12,412 citing papers for an overview of explainable AI research, a perspective on trends using network analysis, and a proposal for best practices and future work in HCI research pertaining to explainability.

Since most of the paper focuses on the literature analysis, the authors highlight only three large areas in their related work section: explainable artificial intelligence (XAI), intelligibility and interpretability in HCI, and analysis methods for trends in research topics.

The major contribution of this paper is a sizable literature analysis of explainable research, enabled by the citation network the authors constructed. Papers were aggregated based on a keyword search on variations of the terms “intelligible,” “interpretable,” “transparency,” “glass box,” “black box,” “scrutable,” “counterfactuals,” and “explainable,” and then pruned down to 289 core papers and 12,412 citing papers. Using network analysis, the authors identified 28 significant clusters and 9 distinct research communities, including early artificial intelligence, intelligent systems/agents/user interfaces, ambient intelligence, interaction design and learnability, interpretable ML and classifier explainers, algorithmic fairness, accountability, transparency, policy, journalism, causality, psychological theories of explanations, and cognitive tutors. In contrast, my work is focused on the research in interpretable ML and classifier explainers for deep learning.

With the same sets of core and citing papers, the authors performed LDA-based topic modeling on the abstract text to determine which communities are related. The authors found the largest, most central and well-studied network to be intelligence and ambient systems. In my research, the most important subnetworks are the Explainable AI: Fair, Accountable, and Transparent (FAT) algorithms and Interpretable Machine Learning (iML) subnetwork and the theories of explanations subnetworks. In particular, the authors provide a distinction between FATML and interpretability; while FATML is focused on societal issues, interpretability is focused on methods. Theory of explanations joins causality and cognitive psychology with the common threads of counterfactual reasoning and causal explanations. Both these threads are important factors in my taxonomy analysis.

In the final section of their paper, the authors name two trends of particular interest to us: ML production rules and a road map to rigorous and usable intelligibility. The authors note a lack of classical AI methods being applied to interpretability, encouraging broader application of those methods to current research. Though this paper focused mainly on setting an HCI research agenda in explainability, it raises many points relevant to my work. Notably, the literature analysis discovered subtopics and subdisciplines in psychology and social science, not yet identified as related in my analysis.

8.3.3 Explanations for Black-Box Models

A recent survey on methods for explaining black-box models [87] outlined a taxonomy to provide classifications of the main problems with opaque algorithms. Most of the methods surveyed are applied to neural-network based algorithms, and therefore related to my work.

The authors provide an overview of methods that explaining decision systems based on opaque and obscure machine learning models. Their taxonomy is detailed, distinguishing small differing components in explanation approaches (e.g. Decision tree vs. single tree, neuron activation, SVM, etc.) Their classification examines four features for each explanation method:

1. The type of the problem faced.
2. The explanatory capability used to open the black box.
3. The type of black box model that can be explained.
4. The type of input data provided to the black box model.

They primarily divide the explanation methods according to the types of problem faced, and identify four groups of explanation methods: methods to explain black box models; methods to explain black box outcomes; methods to inspect black boxes; and methods to design transparent boxes. Using their classification features and these problem definitions, they discuss and further categorize methods according to the type of explanatory capability adopted, the black box model "opened", and the input data. Their goal is to review and classify the main black box explanation architectures, so their classifications can serve as a guide to identifying similar problems and approaches. I find this work a meaningful contribution that is useful for exploring the design space of explanation methods. my classification is less finely-divided; rather than subdividing implementation techniques, I examine the focus of the explanatory capability and what each approach *can* explain, with an emphasis on understanding how different types of explainability methods can be evaluated.

8.3.4 Explainability in Other Technical Domains

Explainable planning [63] is an emerging discipline that exploits the model-based representations that exist in the planning community. Some of the key ideas were proposed years ago in plan recognition [107]. Explainable planning urges the familiar and common basis for communication with users, while acknowledging the gap between planning algorithms and human problem-solving. In this paper, the authors outline and provide examples of a number of different types of questions that explanations could answer, like "Why did you do A" or "Why DIDN'T you do B", "Why CAN'T you do C", etc. In addition, the authors emphasize that articulating a plan in natural language is NOT usually the same thing as explaining the plan. A request for explanation is "an attempt to uncover a piece of knowledge that the questioner believes must be available to the system and that the questioner does not have". I discuss the questions an explanation can and should answer in the conclusion.

Automatic explanation generation is also closely related to computers and machines that can tell stories. In John Reeves' thesis [186], he created the THUNDER program to read stories, construct character summaries, infer beliefs, and understand conflict and resolution. Other work examines how to represent the necessary structures to do story understanding [162]. The Genesis Story-Understanding System [241] is a working system that understands, uses, and composes stories using higher-level concept patterns and commonsense rules. Explanation rules are used to supply missing causal or logical connections.

At the intersection of human robot interaction and story-telling is verbalization; generating explanations for human-robot interaction [191]. Similar approaches are found in abductive reasoning; using a case-based model [132] or explanatory coherence [168]. This is also a well-studied field in brain and cognitive science by filling in the gaps of knowledge by imagining new ideas [147] or using statistical approaches [120].

8.3.5 Explanations for Society

Explanations have been proposed as an artifact to build societal trust. Recent work has looked at ways to correct neural network judgments [251] and different ways to audit such networks by detecting biases [220]. But these judgments are not enough to completely understand the model's decisions-making. Other work answers why questions by finding similar data points [38]. Although these methods are clearly interpretable, they do not provide any unique insights into why the model made those decisions. Other work examining best practices for explanation [206] provides a set of categories, but does not evaluate the questions that explanatory systems should be able to answer; which is necessary for policy makers and societal trust in DNN decision processes.

The desire for explanations in certain sectors of the law is not new. For example, the U.S. Fair Credit Reporting Act creates obligations for transparency in certain financial decision-making processes, even if they are automated [126]. The role of explanation has been examined to enforce accountability under the law [55]. Similar recommendations in using explanations in law have been examined in promoting ethics for design [164], for privacy [165], and liability for machines [231].

In this chapter, I explicitly examine DNNs, even though there have been important developments in explanatory systems not tailored to DNNs, such as randomized importance [144], rule lists [136], partial dependence plots [252, 65, 161], Shapely scores [213, 161], and Bayesian case based models [113].

8.4 Taxonomy

The approaches from the literature that I have examined fall into three different categories. Some papers propose explanations that, while admittedly non-representative of the underlying decision processes, provide some degree of *justification* for emitted choices that may be used as response to demands for explanation in order to build human trust in the system's accuracy and reasonableness. These systems *emulate* the *processing* of the data to draw connections between the inputs and outputs of the system.

The second purpose of an explanation is to explain the *representation* of data inside the network. These provide insight about the internal operation of the network and can be used to facilitate explanations or interpretations of activation data within a network. This is comparative to explaining the internal data structures of the program, to start to gain insights about why certain intermediate representations provide information that enables specific choices.

The final type of explanation is *explanation-producing* networks. These networks are specifically built to explain themselves, and they are designed to simplify the interpretation of an opaque subsystem. They are steps towards improving the transparency of these subsystems; where processing, representations, or other parts are justified and easier to understand.

The taxonomy I present is useful given the broad set of existing approaches for achieving varying degrees of interpretability and completeness in machine learning systems. Two distinct methods claiming to address the same overall problem may, in fact, be answering very different questions. My taxonomy attempts to subdivide the problem space, based on existing approaches, to more precisely categorize what has already been accomplished.

I show the classifications of my reviewed methods per category in Table 8.1. Notice that the processing and explanation-producing roles are much more populated than the representation role. I believe that this disparity is largely due to the fact that it is difficult to evaluate representation-based models. User-study evaluations are not always appropriate. Other numerical methods, like demonstrating better performance by adding or removing representations, are difficult to facilitate.

The position of my taxonomy is to promote research and evaluation across categories. Instead of other explanatory and interpretability taxonomies that assess the purpose of explanations [54] and their connection to the user [1], I instead assess the focus on the method, whether the method tries to explain the *processing* of the data by a network, explain the *representation* of data inside a network or to be a self-explaining architecture to gain additional meta predictions and insights about the method.

I promote this taxonomy, particularly the explanation-producing sub-category, as a way to consider designing neural network architectures and systems. I also highlight the lack of standardized evaluation metrics, and propose research crossing areas of the taxonomy as future research directions.

Processing	**Representation**	**Explanation Producing**
Proxy Methods	Role of layers	Scripted conversations
Decision Trees	Role of neurons	Attention-based
Salience mapping	Role of vectors	Disentangled rep.
Automatic-rule extraction		Human evaluation

Table 8.1: The classifications of explanation methods by the *focus* of the explanation.

8.5 Evaluation

Although I outline three different focuses of explanations for deep networks, they do not share the same evaluation criteria. Most of the work surveyed conducts one of the following types of evaluation of their explanations.

1. Completeness compared to the original model. A proxy model can be evaluated directly according to how closely it approximates the original model being explained.

2. Completeness as measured on a substitute task. Some explanations do not directly explain a model's decisions, but rather some other attribute that can be evaluated. For example, a salience explanation that is intended to reveal model sensitivity can be evaluated against a brute-force measurement of the model sensitivity.

3. Ability to detect models with biases. An explanation that reveals sensitivity to a specific phenomenon (such as a presence of a specific pattern in the input)

can be tested for its ability to reveal models with the presence or absence of a relevant bias (such as reliance or ignorance of the specific pattern).

4. Human evaluation. Humans can evaluate explanations for reasonableness, that is how well an explanation matches human expectations. Human evaluation can also evaluate completeness or substitute-task completeness from the point of view of enabling a person to predict behavior of the original model; or according to helpfulness in revealing model biases to a person.

The trade-off between *interpretability* and its *completeness* can be seen not only as a balance between simplicity and accuracy in a proxy model. The trade-off can also be made by anchoring explanations to substitute tasks or evaluating explanations in terms of their ability to surface important model biases. Each of the three types of explanation methods can provide explanations that can be evaluated for completeness (on those critical model characteristics), while still being easier to interpret than a full accounting for every detailed decision of the model.

8.5.1 Processing

Processing models can also be regarded as emulation-based methods. Proxy methods should be evaluated on their faithfulness to the original model. A handful of these metrics are described in [189]. The key idea is that evaluating completeness to a model should be local. Even though a deep neural network, is too complex globally, you can still explain in a way that makes sense locally by approximating local behavior. Therefore, processing model explanations want to minimize the "complexity" of explanations (essentially, minimize length) as well as "local completeness" (error of interpretable representation relative to actual classifier, near instance being explained).

Salience methods that highlight sensitive regions for processing are often evaluated qualitatively. Although they do not directly predict the output of the original method, these methods can also be evaluated for faithfulness, since their intent is to explain model sensitivity. For example, [8] conducts an occlusion experiment as ground truth, in the model is tested on many version of an input image where each portion of the image is occluded. This test determines in a brute-force but computationally inefficient way which parts of an input cause a model to change its outputs the most. Then each salience method can be evaluated according to how closely the method produces salience maps that correlate with this occlusion-based sensitivity.

8.5.2 Representation

Representation-based methods typically characterize the role of portions of the representation by testing the representations on a transfer task. For example, representation layers are characterized according to their ability to serve as feature input for a transfer problem, and both Network Dissection representation units and Concept Activation Vectors are measured according to their ability to detect or correlate with specific human-understandable concepts.

Once individual portions of a representation are characterized, they can be tested for explanatory power by evaluating whether their activations can faithfully reveal a specific bias in a network. For example, Concept Activation Vectors [112] are evaluated by training several versions of the same network on data sets that are synthesized to contain two different types of signals that can be used to determine the class (the image itself, and an overlaid piece of text which gives the class name with varying reliability). The faithfulness of CAVs to the network behavior can be verified by evaluating whether classifiers that are known to depend on the text (as evidenced by performance on synthesized tests) exhibit high activations of CAV vectors corresponding to the text, and that classifiers that do not depend on the text exhibits low CAV vectors.

8.5.3 Explanation-Producing

Explanation-producing systems can be evaluated according to how well they match user expectations. For example, network attention can be compared to human attention [46], and disentangled representations can be tested on synthetic data sets that have known latent variables, to determine whether those variables are recovered. Finally, systems that are trained explicitly to generate human-readable explanations can be tested by similarity to test sets, or by human evaluation.

One of the difficulties of evaluating explanatory power of explanation-producing systems is that, since the system itself produces the explanation, evaluations necessarily couple evaluation of the system along with evaluation of the explanation. An explanation that seems unreasonable could indicate either a failure of the system to process information in a reasonable way, or it could indicate the failure of the explanation generator to create a reasonable description. Conversely, an explanation system that is not faithful to the decision making process could produce a reasonable description even if the underlying system is using unreasonable rules to make the decision. An evaluation of explanations based on their reasonableness alone can miss these distinctions. In [54], a number of user-study designs are outlined that can help bridge the gap between the model and the user.

8.6 Societal Expectations for Explanations

Imagine you do not receive a loan, you would want to know what was the key attribute that limited the algorithm. You would want to know *why* you were denied a loan. But further, you may also want a sensitivity analysis: what would you need to change to be able to get the loan. There may be several possibilities. For example, you may have received a loan if you made $1,000 more per month; something you may be able to change in the future. However, other factors may be things you cannot control, such as the specific time you applied or your gender or ethnicity. So, in this case, we would like to have system that is able to explain why it decided to give or not a loan to each person.

Moreover, consider again the AI system example mentioned earlier of a self-driving car involved in an accident. The first thing we would want to know is why the accident happened. In this case there are many algorithms interacting. Finding if there was a faulty component is extremely challenging, making it even more relevant for each part of the system to be able to explain its decisions. In the recent Uber accident where the vehicle struck and killed a pedestrian, detecting the root-cause of the accident took several weeks to uncover in the complex AI software system [151, 150].

But the other, more challenging question we would want to ask is if the accident could have been avoided. This is a more difficult question than the previous, single algorithm question. In complex systems, an error could be local (caused by a single failure), or it could be caused by an inconsistency between parts working together. The latter is much more difficult to detect, diagnosis, and explain.

In the Uber case, since the accident was caused by a false positive [134] on the error detection monitoring the pedestrian, several explanations could provide evidence of how this could have been avoided. Again, some inconsistencies are easier to fix than others (which may not be possible). Perhaps the sensitivity on the error detection monitor should be decreased or increased. Or perhaps the pedestrian would have been detected with higher certainty during the daytime, or if they were walking slower. It is still left to question whether the training data was at fault, which introduces a new set of questions.

8.6.1 Definitions

I follow the definition from Section 8.1.2 that a proper explanation should be both interpretable and complete. By interpretable, I mean that the explanation should be understandable to humans. That does not necessarily imply that the explanation must be in human-readable form, in fact, visual cues are well-understood by humans. When I say that the methods must be complete, I mean the resulting explanation should be true to the model. For example, while using a simplified model that is explainable (like a linear model) to fit the input to the output results in a nice explanation, it is not a true and complete representation of the internal concepts, representations, and decisions of the model.

I refer to *inside* and *outside* explanations for explaining DNNs. When I refer to inside explanations, I am referring to the type of explanations that currently exist, that are catered towards AI developers and experts. They are tailored to people

Table 8.2: Strengths, benefits, and challenges of current DNN XAI systems

Method	**Questions it can answer**	**Questions it cannot answer**
Processing	Why does this particular input lead to this particular output?	Why were these inputs most important to the output? How could the output be changed?
Representation	What information does the network contain?	Why is a representation relevant for the outputs? How was this representation learned?
Explanation producing	Given a particular output or decision, how can the network explain its behavior?	What information contributed to this output/decision? How can the network yield a different output/decision?

inside the field. We encourage the development of *outside* explanations that are interpretable, complete, and answer why questions. They build trust not only to their technical developers, but also those *outside* the technical scope that may use their technology without a technical background.

8.6.2 Current Limitations

To show the strengths, benefits, and challenges of current explanatory approaches for opaque, DNN systems, I use the taxonomy from Section 8.4 [76] . The taxonomy consists of 3 classes. The first class are systems that explain processing by looking at the relationships between the inputs and the outputs. These include salience mapping [254, 203], decision trees [257], automatic rule-extraction [9], and influence functions [119]. The second class are systems that explain representation for DNNs either in terms of layers [185, 245], neurons [19] or vectors [112]. The final class is explanation-producing systems that look at attention-based visual question answers [174] or disentangled representations [194] to create self-explaining systems.

When examining this taxonomy for policy purposes, the biggest shortcoming is that these systems cannot explain *why*. There are two types of questions that we should ask of a decision making algorithm:

1. Why did this output happen?

2. How could this output have changed?

A summary of the types of questions that current DNN XAI systems can and cannot answer are in Table 8.2. Explanation producing systems nearly answer the first question we would want to ask a decision making algorithm: why did this output happen? But the problem is that their explanation may not be *complete* and *true* to the model's internal decisions and processes.

8.7 A Big Problem: Opaque Perception Processes

Some of the best performing AI mechanisms are opaque. I showed how to monitor these approaches in Chapter 4, most complex statistical computations are not explainable. Although some "concept-level" explanations exist [112, 19], these are based on partial explanations are a set of numerical weights. There is immediate "story" available.

But humans have the same problem. We cannot make a symbolic justification of a perception. If we perceive something hazardous, such as the smell of smoke in a building, we cannot explain why. However, we are able to describe this perception in the context of a longer story: "There are many people in my apartment. I smelled smoke and so I told the occupants to evacuate." Every decision or action may depend on some primitive perceptions but the combination that led to the result can be explained, if we have the right symbolic descriptions for the primitive perceptions. In the next few sections, I describe methods that attempt to "fill in the gaps" of perception.

8.7.1 Hallucinating Information

Expectation is essential to perception. The idea is that the expectation generates a "hallucination:" a reasonable interpretation of constrained sensory data. In fact, Andy Clark has said that “Perception itself is a kind of controlled hallucination”[7]. Beale and Sussman actually showed a proof-of-concept of this idea [20]. Computers struggle to perceive Kanizsa’s triangle or other illusionary contours that are are visible to humans. Humans can also “fill in the gaps” and use context to classify blurry photos [224].

The key idea is that expectation needs to be constructed in a way that is analogous to the domain-specific language. Consider the domain of stage-acting. Scene descriptions (the domain-specific language) describe the characters and how they appear (e.g. “Hamlet enters stage right”. This description produces an expectation that is aligned with our perception.

8.7.2 Imagining Possible Futures

Sound decisions are not made based on some single instant in time; rather, they are made with careful consideration of their consequences. Sometimes these consequences may not be known beforehand. This was stated nicely by Donald Rumsfled[8]:

> There are known knowns. These are things we know that we know. There are known unknowns. That is to say, there are things that we know we don’t know. But there are also unknown unknowns. There are things we don’t know we don’t know.

Thus, a system must be able to imagine each possible future that may result from its choices, and evaluate whether that future might be reasonable. To do this well, the system must be able to *simulate* the behavioral and physical consequences of acting on any set of premises that may be chosen by committee arbitration, particularly in the case where it will have accepted premises that in fact represent the wrong situation.

Given a set of premises whose relative validity may not be obvious, it can be difficult to decide which premises to accept. There are of course situations in which

[7]`https://www.edge.org/conversation/andy_clark-perception-as-controlled-hallucination`

[8]Gerald Jay Sussman introduced me to this idea of “Rumsfledian reasoning.”

premises can be identified as faulty – for example, if they lead to violations of reasonableness constraints or contradictions of systematic axioms. Often, though, we cannot reject any of the available premises outright. In such cases we need a way to decide which system of premises, out of equally plausible-looking possibilities, is to be accepted in practice – and, as a corollary, what future our system pursues.

One can try to treat this problem as one of simulation-based *search*, with a possible objective being to find the choice of premises resulting in the "least bad" set of consequences given the set of possible realities under consideration. It is of course impossible to consider every potentially available reality; for instance, one cannot, in this process, reasonably account for events like a meteor strike during the interval under consideration, where no evidence exists to support the notion of incoming meteors. However, information reported by onboard perception supporting the existence of an "unusual" object, like a lawnmower, provides at least two possibilities – the existence of a lawnmover, or a defect in the onboard perception – whose consequences must be examined.

8.7.3 Commonsense Reasoning

Humans are opaque systems. When something goes wrong, we cannot always say why. For example, when we are ill or malfunctioning, we cannot always point to the exact subsystem causing the error. But we can form a coherent explanation of what we *believe* we are suffering from, by querying previous data and commonsense. If we have a fever, we can usually come up with a reason: we feel hot, then cold, and that is *similar to* a previous time when we had a fever. We can also create explanations with commonsense. If we have a stomach ache, perhaps it was the spicy food that caused the pain. Or, it was the fact that we ate a heavy meal on a previously [starved] stomach.

One way to mitigate perception errors is to supplement decisions with commonsense. For example, in the stomach ache example, we can use commonsense to come up with multiple explanations. This requires the availability of a commonsense knowledge base. I can formulate explanations using "nearby" information: the stomach is close to the appendix, which may be ruptured. Or we can create other causal explanations: stomach aches can be caused by spicy food, or stomach aches can be caused by eating too much on an empty stomach. It is difficult to determine which one of these explanations is "most" correct or plausible, which is left to future work. But, the ability for intelligent machines to use commonsense to formulate these explanations themselves is a promising area of research.

8.8 The Risk of Deploying Opaque Models

Generally explaining model behavior is not enough to build trust in these sorts of models. Another way these algorithms and systems can behave badly is due to a inconsistency in the training data and/or knowledge bases. This does not necessarily mean that the training data is "bad" per say, but that there is a misalignment between the expected data and the actual training data used. We have seen this recently with the Amazon recruiting algorithm [47]. This algorithm was eventually disbanded because the results were extremely biased; since the algorithm had been trained on applicants data for the past 10 years (where males are dominant), it was teaching itself to choose male candidates. Even if the algorithm was modified, there was no way to ensure it was unbiased. Although this is an extremely compelling case for inquisitive explanatory systems, an even more persuasive case is for safety-critical tasks.

Consider a machine learning classifier to diagnose breast cancer from an image, where the training set was carefully selected to be fairly close to a 50-50 split of breast cancer and non-breast cancer scans. Even if the classifier is very accurate, without having access to complete explanations to understand how decisions are made in the model, it is not certain that it is making decisions for the right reasons—the model may in fact, learn a feature it should not rely on despite predicting breast cancer very accurately. In [106], one classifier learned the resolution of the scanner camera, therefore predicting cancerous images from a high resolution very accurately. Figuring out this sort of data problem is extremely difficult. It requires either an attuned intuition of the model's inner workings or the model to be able to answer questions to do a fine-grain sensitivity analysis.

8.9 Conclusions

One common viewpoint in the deep neural network community is that the level of interpretability and theoretical understanding needed to for transparent explanations of large DNNs remains out of reach; for example, as a response to Ali Rahimi's Test of Time NeurIPS address, Yann LeCunn responded that "The engineering artifacts have almost always preceded the theoretical understanding" [133]. However, I assert that, for machine learning systems to achieve wider acceptance among a skeptical populace, it is crucial that such systems be able to provide or permit satisfactory explanations of their decisions. The progress made so far has been promising, with efforts in explanation of deep network processing, explanation of deep network representation, and system-level explanation production yielding encouraging results.

I find, though, that the various approaches taken to address different facets of explainability are siloed. Work in the explainability space tends to advance a particular category of technique, with comparatively little attention given to approaches that merge different categories of techniques to achieve more effective explanation. Given the purpose and type of explanation, it is not obvious what the best type of explanation metric is and should be. I encourage the use of diverse metrics that align with the purpose and completeness of the targeted explanation. My position is that, as the community learns to advance its work collaboratively by combining ideas from different fields, the overall state of system explanation will improve dramatically, resulting in methods that provide behavioral extrapolation, build trust in deep learning systems, and provide usable insight into deep network operation enabling system behavior understanding and improvement.

Chapter 9

Contributions and Future Work

"Human beings are symbolic creatures. Inside their heads they break down the outside world into a mass of mental symbols, then recombine those symbols to recreate that world."[1]

– Ian Tattersall via Patrick Henry Winston

Failures in autonomous machines, whether fatal[2] or uncomfortable[3], are due to mistakes that a human would never make. Such increased level of harm on human lives is undesirable and completely untenable. Consequently, assessing pre-deployment reliability is important for autonomous agents that are responsible for decisions in critical settings. One solution is to provide a reason or justification for the decision of the autonomous agent being assessed: an explanation. But most of these explanations are static, and not *representative* of the underlying agent's processing.

In this thesis, I present a novel methodology, implementation, and evaluation that utilizes explanations in two distinct ways. System-wide explanations are provided to an end-user for analysis, while internal explanations are used among subsystems to defend their actions and ensure robust higher-level decisions. Therefore, I differentiate between (i) an internal subsystem explanation (or internal explanation), the

[1]This quote is from Patrick H. Winston's last public talk at the celebration of MIT's new Swartzman College of Computing. Available at: `https://people.csail.mit.edu/phw/video/NewCollegeTalk.mp4`

[2]An uber self-driving vehicle strikes and fatally kills a pedestrian [151].

[3]Mall robot injures a toddler: `https://qz.com/730086/a-robot-mall-cop-did-more-harm-than-good/`

symbolic reasons and dependencies for a specific local subsystem's behavior, and (ii) a system-wide narrative explanation (or system explanation), a (mostly causal) chain of reasoning generated from the underlying subsystems. Since the underlying reasons and dependencies are symbolic, they can be translated into a human-understandable explanation with various degrees of detail: for anomaly detection, legal analysis, and diagnosis.

My thesis contributes a new perspective on anomaly detection. Instead of viewing anomalies as outliers in some coordinate system, I define anomalies as circumstances which cannot be explained away by a consensus of neighboring subsystems. If a subsystem provides an explanation that is inadequate or inappropriate, the subsystem should either be corrected or disabled. In Chapter 7, I applied this methodology to an autonomous vehicle. Through simulated erroneous test cases, I demonstrated that ADE can reconcile inconsistencies between subsystems by examining the underlying subsystem explanations. The key idea is that ADE is a general methodology; all complex mechanisms should have the ability to reason, abstract from data, and explain their behavior. Imagine if computer debugging was *communicative*: the computer works *with* the human user to reconcile and diagnose errors. Computers could teach their human counterparts new skills by *explaining* themselves clearly and coherently.

9.1 Explanations as a Debugging Language

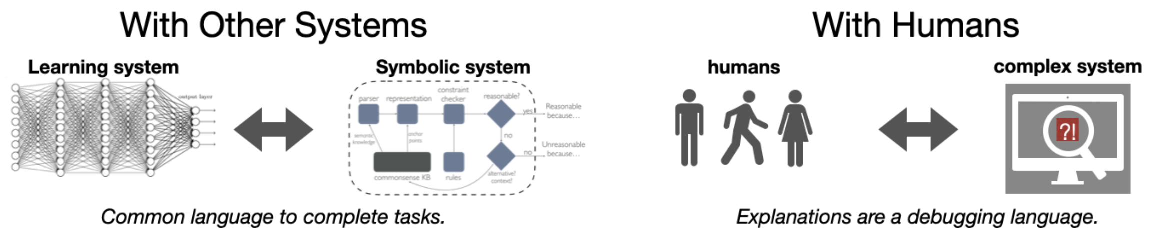


Figure 9-1: My vision for articulate machines that can coherently communicate to each other and to a human.

In Chapter 7, I used internal explanations as a debugging language between subsystems. But the larger goal is to facilitate better communication amongst subsystems. In fact, there is limited internal reasoning and communication amongst the subsystems of a complex machine. One reason is that the subsystems speak different languages. In Chapter 5, I showed the log traces from a sensor and how those low-level "point clouds" are quite different from the high-level vision processing labels. However, LiDAR and vision systems are both *perceiving* the world. Even though they process perception at different levels of abstraction, both systems should be able to reason about their results in the same language.

I view symbolic reasons, justifications, and explanations as a communication language. My vision is two-fold, as seen in Figure 9-1. On the left, I argue that system-level explanations can facilitate better communication among systems to complete tasks, e.g., a hybrid reasoning system, described in Section 9.2.1. On the right, I argue that explanations are a debugging language, for systems and tasks that include people. I discuss some of these tasks in Section 9.3.1.

In this thesis, I developed symbolic systems to monitor opaque learning systems, but the symbolic systems do not currently change the internal state of the opaque learning system. However, imagine if they could *learn* from each other. Symbolic systems excel at abstraction, while learning systems excel at finding trends in data. What if they could work together and communicate between themselves to infer abstract trends in data? I believe that combining symbolic and learning approaches, by facilitating a communication language for them to work together, is a concrete step towards artificial intelligence [156][4].

9.2 Future Applications

My research vision is for complex machines to be *articulate by design*. Dynamic internal explanations will be part of the design criteria, and system-level explanations will be able to be challenged in an adversarial proceeding. Further, explanations are dynamic: if the explanation is inadequate or inappropriate, the underlying pro-

[4]Examining Minsky's classic steps towards artificial intelligence paper, there are both symbolic *and* data-driven learning approaches. If we are to learn anything from Minsky, it is that neither approach can solve all the AI problems alone.

cess should be corrected or disabled. With this vision, all machines will be able to explain themselves at various levels of detail. This requires progress in reasoning and representation, narrative intelligence and natural language processing (NLP), and human-centered computing. These types of articulate systems are applicable to many domains, including computer security (see Section 9.2.4).

9.2.1 Hybrid Approaches to Intelligent Systems

In critical applications, multiple methods are used to check and validate solutions. The financial realm has double-entry bookkeeping, and airplanes have multiple engines and checks for safety-critical components. We should also require machines to be able to reason about their decisions in multiple ways. But reasoning systems and approaches currently function in isolation. My work relies on techniques from commonsense reasoning, case-based reasoning, and hypothetical reasoning. Many of these techniques are used in isolation, but as a first step, I will try to incorporate these approaches together in a hybrid-reasoning system that uses rules, commonsense, and hypotheticals for more robust decision making.

Systems that use higher-level representations are restrictive; they are typically human-curated, static, and specific to the target application or input data. In my reasonableness monitoring system [74], I represented the input descriptions as a composition of conceptual primitives. This representation is difficult to learn automatically. As a first step, I will look at more flexible representations of knowledge and language, and how representations can be learned with limited human-curated information.

9.2.2 Using Explanations as Internal Narrative

Machines should be able to tell stories like people do. The types of explanations that I develop serve two purposes: their symbolic representation is used internally by the parts of a machine to reconcile their errors, and is then constructed into a human-readable explanation documenting what happened and why. Processing, understanding, and building these types of explanations is still an open area of research.

9.2.3 Explanations for Society

When autonomous machines share control with a human operator, there will be some explaining to do. If the autonomous operator intervenes, the human will ask why. If the machine operator does not provide a proper explanation, the collaboration will be flawed. They will need to speak a common language, and be able to process, understand, interpret, and intervene based on this language in real-time. I am interested in using explanations shared between a human and machine operator for more streamlined and trustworthy decision making. This relies on better system design and mechanisms for humans to intervene based on explanations.

Another societal problem is that the legal realm does not support the upcoming transition to autonomous decision making (e.g., AVs). These decision making systems have been shown to cause harm, including racial bias [237] and in some cases even physical harm. In safety-critical and mission-critical decisions, AVs will need to be able to defend their actions and testify in an adversarial proceeding. As an interdisciplinary direction, I could encode the legal requirements for these machines to be able to explain themselves to abide by legal rules and infrastructure.

In this thesis, I created a system architecture that is inspired by the structure of human committees. The methodology can be applied to complex human organizations: imagine a social or government structure where every intended action is supplemented with a corresponding reason. Inconsistencies amongst committees are reconciled by comparing the committees' proposed actions and their underlying justifications to a priority hierarchy. Automatic reasoning and negotiation (with explanations) will help to mitigate societal conflicts.

9.2.4 Security Applications

Computer security systems are imperfect. Intrusion detection software is good at catching single points of failure and other local vulnerabilities, but most security software fails when there is a faulty connection or an *inexplicable communication* between parts. Using symbolic subsystem explanations can mitigate these intrusions by constantly and consistently monitoring the reasonableness of subsystem communication and checking the behavior against prior data. This approach is also relevant for IoT systems, in which independent entities work together, making common communication key to diagnosing errors.

9.3 Reevaluating Evaluations

A common question is "who is the explanation for?" This is a difficult question to answer because it depends on the applications and the use case. For the critical, self-driving application, I argue that the explanations are for the machine: they are used as evidence to reconcile system-wide errors. I argue that the type of evaluation is dependent on *what* the explanation is actually explaining (see Table 8.1). Since my explanation procedures are explaining inconsistencies, it is important to consider the types of *tasks* where these explanations are essential. In this section, I propose tasks that require explanations: software debugging, collaborative games, and autonomous vehicle challenges.

9.3.1 Tasks that Require Explanations

A way to evaluate explanations is to design tasks that rely on explanations to be completed. For example, a task for which a human operator and computer system have to work together, and the explanations (from and to a human) are necessary for task completion. A nice example would be computer debugging, where the error is communicated through a series of explanations from a computer. The debugging program and the human communicate back and forth until the root cause is correctly identified. Other types of collaborative tasks would also be reasonable benchmarks.

Hanabi is a collaborative card game. It has recently been proposed as an important new challenge for artificial intelligence [18]. It has imperfect information, as the players can view other players' cards but not their own. The goal is to play a series of cards in a specific order, and players are allowed to give information to each other in a specific language. This game has been solved mathematically [43], but I argue that it is still an important task due to the fact that collaboration is necessary to succeed. Further, self-explanation is important in these kinds of games, and in card games in general. In poker, expert players use a "theory of mind"[5].

9.3.2 Challenges for Imagining and Explaining Possible Futures

Human drivers are able to reason about circumstances they have not seen before, exactly the ones that confound autonomous vehicles. But these "difficult autonomous scenarios," are not yet characterized or bench-marked. I argue that careful writing of challenge scenarios will ensure safety, trust, and reliability in widespread autonomous vehicle adoption.

There is a complete void of erroneous autonomous vehicle data. The current self-driving data sets are hand-curated and perfectly labeled [31, 110, 69]. Autonomous driving challenges[6] are vaguely constructed (e.g., avoid a neighboring car or switch lanes), but a successfully completed challenge would be precise in execution. The successes of autonomous vehicles are completely dependent on their ability to learn through (previously observed) experiences. Instead, I aim to create a set of self-driving error scenarios that require abstract, high-level anticipatory thinking: the same type of reasoning humans do in difficult situations. In the same way humans can learn without experiencing, I will develop scenarios that ensure autonomous vehicles can also learn new things, without failing first.

These challenges may include meta-tasks like theory of mind (e.g., what is the neighboring vehicle trying to accomplish) or self-introspection (e.g., after observing a new highway sign, retroactively analyzing one's actions). These error scenarios, although not fully representative of all the failure cases, will encapsulate the types

[5]Poker players using theory of mind to imagine their opponents `https://www.forbes.com/sites/alastairdryburgh/2015/08/20/how-theory-of-mind-can-make-or-lose-you-money`

[6]Carla autonomous driving challenge scenarios: `https://carlachallenge.org/challenge/nhtsa/`

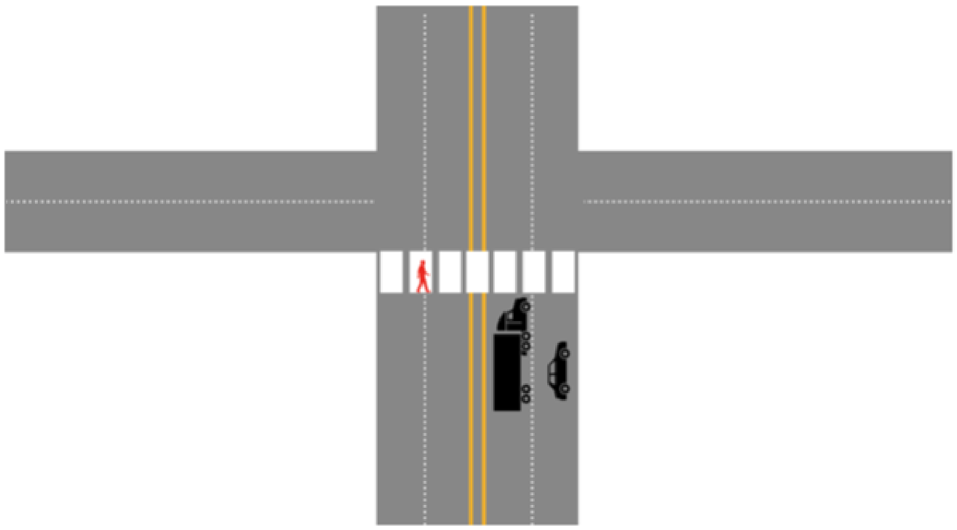


Figure 9-2: A difficult driving scenario for a self-driving vehicle.

of abstract anticipatory thinking that autonomous machines (and especially vehicles) need to possess for safety-critical or mission-critical tasks. Developing this capability results in adaptive autonomous vehicles that can reason and address the ever-growing long tail of errors.

Consider the cross-walk example in Figure 9-2. Large trucks typically block the field of view of neighboring drivers. In suburban areas, the truck may block a pedestrian or another critical, moving object. Human drivers can "imagine" this scenario, but autonomous agents cannot. The key question is how an autonomous agent could "haluccinate" this hidden threat, especially if it has not seen it before. This is a scenario that requires abstract reasoning and anticipatory thinking[7].

Other difficult scenarios are "corner cases" that humans learn from experience. Consider an autonomous vehicle stopped on an incline. When I was learning to drive in San Francisco (a city that is known for its hills), I was shocked to learn that you want to engage the brakes and the gas at the same time when accelerating up a hill from a stop. It is left to consider whether this type of behavior could be learned. But these types of intuitive physics "corner cases" are important to reason about, especially in difficult driving conditions.

[7]The idea of Anticipatory Thinking (AT) is an emerging area. I have been defining this idea in terms of autonomous vehicle challenge problems: `https://www.anticipatorythinking.ai`.

9.4 Implications

My thesis contributes a new vision of anomaly detection; in which anomalies are not outliers, but instances that cannot be explained away by the consensus of neighboring parts. These errors are actually beneficial for the system, and can be used to mitigate future problems. For example, if LiDAR fails when it is raining, then the high-level planner can discount the LiDAR component in inclement weather. If the vehicle continuously skids on left turns, then parts that contribute to the turning sequence (e.g., the tires, vehicle alignment, brakes, steering, power control, etc.) can be re-evaluated. If the vision system consistently confuses turtles with weapons [14], then it should have to *explain why*. It is only in the case where the machine cannot explain its failure that the error becomes a bug.

I have presented two ideas towards system-wide anomaly detection. First are sanity checks, or reasonableness monitors, that uphold subsystems to a set of reasonable rules and behaviors. Second is to facilitate better communication amongst parts through explanation. When those two ideas are combined into a system-wide architecture, namely Anomaly Detection Through Explanations (ADE) in Chapter 7, I discovered that explanations facilitate a common debugging language for inconsistencies amongst subsystems.

My work has opened up the new area of explanatory anomaly detection, towards a vision in which: complex mechanisms will be articulate by design; dynamic, internal explanations will be part of the design criteria, and system-level explanations will be able to be challenged in an adversarial proceeding. I have discussed how these explanations aid in system-level debugging, but imagine a world in which an autonomous agent can defend itself. The system-wide explanations are a story: an unbiased account of what happened and why. By querying the explanation synthesizer, information can be retracted and added; possibly creating a way to fix a formerly broken complex machine. While not all complex machines will work this way, it ensures safer, more robust monitored machines in safety-critical and mission-critical tasks.

In summary, autonomous agents are making *decisions with consequences*. For stakeholders (e.g., insurance companies, police overseers) and society (e.g., the people who may be harmed) to trust these autonomous thought-partners, the agents need to provide concise and understandable explanations of their actions. This explanatory ability requires significant technical developments in reasoning, representation, and narrative, while also exploring societal questions in HCI and policy-making. In the current interim of shared autonomy (between human and machines), a path of adoption includes the use of monitoring, learning from explanations, and adaptable representations towards system-wide deployment of self-explaining systems. By focusing on limited autonomy, like a car that drives itself, complex machines are learning details and trends rather than abstracting and learning from their mistakes. Instead, my approach is to create the capability for a complex machine, like a car, to be aware of its internal state as well as its environment. In other words, a car that knows and can explain that it is driving.

9.5 A Salute

In Patrick Winston's "How to Speak" lecture, he suggested that you end each talk (or document) with a salute. The salute thanks the audience (or the reader) for their attention, questions, and participation.

I have been fortunate to work on a problem that is unsolved. Errors in autonomous vehicles, whether fatal [151] or uncomfortable[8], are difficult to represent. In fact, there is a complete void of erroneous autonomous vehicle data. The current self-driving data sets are hand-curated and perfectly labeled [31, 110, 69]. At the same time, current challenges[9] are vague in approach, but precise in execution. In my thesis work, I have defined a methodology for complex machines to reason about their own errors. It utilizes abstract, high-level reasoning; the same type of reasoning humans do in difficult situations.

[8]Consistent starting and stopping self-driving behavior: `https://www.wired.com/story/ride-general-motors-self-driving-car/`.

[9]NTHSA inspired autonomous vehicle challenges: `https://carlachallenge.org/challenge/nhtsa/`.

I have evaluated my methodology on simulated errors. In ongoing work, I will create a set of self-driving error scenarios that embed abstract, high-level anticipatory thinking. These challenges may include meta-tasks like theory of mind (i.e. what is the neighboring vehicle trying to accomplish) or self-introspection (i.e. in new experiences, how does one reason to itself). These error scenarios, although not fully representative of all the failure cases, will personify the types of abstract, anticipatory thinking that autonomous machines (and especially vehicles) need to possess for safety-critical or mission-critical tasks. This long list of errors demonstrates that complex machines need the ability to reason, abstract, and explain.

I alluded that this section is a salute, which thanks the reader. At his last public lecture, my mentor Patrick Henry Winston said, "Now that's the end of my story for today, but I hope it will be just the beginning of a story that will be told in the days and years to come"[10]. But this is not the end of the story, as Neil Gershenfeld[11] once said: a thesis is not finished, rather, it is abandoned. And while there are many more errors to justify, machines to monitor, and rules to learn; I leave the next explanation to a curious reader.

[10]This quote is from Patrick Henry Winston's last public lecture: `https://people.csail.mit.edu/phw/video/NewCollegeTalk.mp4`. This thesis greatly benefited from his guidance and leadership.

[11]I learned "How To Make Almost Anything" from Professor Gershenfeld: `http://ng.cba.mit.edu`. In this course, I witnessed, debugged, and made complex machine errors, first hand.

Appendix A

Auxiliary Information

A.1 Qualitative Algebras

- The *qualitative increment* algebra is essentially a qualitative description of the first derivative. In this chapter, these qualitative descriptions of the first derivative were sufficient to explain the vehicle phenomena. However, for future work, I may need to use more precise quantitative descriptions. In anticipation, I developed a system to keep track of derivative values on the cells in the art of the propagator system.

- The *qualitative action* describes mechanical changes within an interval as a set of four actions: tightening, loosening, no action, and unknown action. It may appear as if the qualitative action is unnecessary, since it has a surjective mapping to the qualitative increment, where tightening is a qualitative increment value of increasing, loosening is a qualitative increment value of decreasing, no action maps to no change, and unknown action maps to unknown change. However, having the qualitative action makes our explanations much easier to report: while the description of "tightening a caliper" is easy to understand, "increasing a caliper" is a bit ambiguous.

- The *qualitative direction* has two values: an incremental change description and a direction description. The incremental change is defined as the qualitative increment. The second value, the direction description, describes a lateral direction in four values: left, right, neutral, and unknown direction. This direction is with respect to a point of reference. In our research, the point of reference is usually the center of mass of the vehicle.

- The *qualitative position* also has two values: a lateral description and a longitudinal description. The lateral description is defined with respect to the direction description defined in the qualitative direction. The longitudinal direction is defined with respect to four values: front, back, neutral and unknown.

After defining the algebras, it is necessary to define the combinations of these values so that the algebraic descriptions can work together to provide a comprehensive explanation. It then becomes important to define the resulting qualitative type from different combinations, so if two qualitative values are added, the resulting qualitative value makes sense. For example, if a qualitative increment and a qualitative action are added together, the resulting value with be a qualitative increment, because the qualitative action can be directly mapped to the qualitative increment. An example additive algebraic function for the `qualitative-direction` is shown in Figure A-1. Since there are only one type of combinations of different qualitative algebras in our model so far: combining qualitative increments and qualitative actions, defining a qualitative hierarchy is left to future work[1].

[1]It is an open problem to create an *ontology* or organization of qualitative values. In fact, most ontologies are domain-dependent, which is why I defined four different qualitative values for *vehicle* changes.

```
(define (add-qualitative-direction x y)
  (let ((x-desc (qualitative-direction-description x))
        (y-desc (qualitative-direction-description y))
        (x-turn (qualitative-direction-turn x))
        (y-turn (qualitative-direction-turn y)))
    (let ((added-desc (qualitative-description
                          (generic-+ (make-qualitative x-desc)
                                     (make-qualitative y-desc)))))
      (cond ((equal? x-turn y-turn)
             (make-qualitative-direction added-desc x-turn))
            ((or (equal? x-turn '?) (equal? y-turn '?))
             (make-qualitative-direction added-desc '?))
            ((equal? x-turn '0)
             (make-qualitative-direction added-desc y-turn))
            ((equal? y-turn '0)
             (make-qualitative-direction added-desc x-turn))
            (else (make-qualitative-direction added-desc '?))))))
```

Figure A-1: An example of qualitative addition for the qualitative direction algebra.

A.2 Conceptual Primitive Descriptions

- *PTRANS*: The PTRANS act primitive represents the event of a thing changing location from one place to another. The PTRANS act typically has an object case, representing the thing which moved or was moved, an actor case representing the actor which performed or caused the movement, and a direction case indicating the start and end point of the movement.

- *MOVE*: The MOVE act primitive represents the event of a thing moving a part of its body or part of itself. The MOVE act has an object case, representing the body part that was moved, an actor case representing the actor which performed the MOVE, and a direction case indicating the start and end point of the movement.

- *PROPEL*: The PROPEL act primitive represents the event of a thing applying a force to another thing, or a moving thing striking or impacting another thing. The PROPEL act typically has an object case, representing the object which was struck or has a force applied to it, an actor case representing the actor which performed or caused the PROPEL, and a direction case indicating the direction of the force.

- *INGEST*: The INGEST act primitive represents the event of a thing moving, being forced, or forcing itself to go from the outside to the inside of another thing.

  The INGEST act has an object case, representing the thing which moved or was moved to the inside of another thing, an actor case representing the actor which performed or caused the movement, and a direction case indicating the start and end point of the movement. Often the end point of an INGEST is a part of the body of the actor. Eating, for example, is an INGEST of something where the end point of the object's movement is the mouth or stomach of the actor.

- *EXPEL*: The EXPEL act primitive represents the event of a thing moving, being forced, or forcing itself to go from the inside to the outside of another thing. The EXPEL act has an object case, representing the thing which moved or was moved from inside to the outside of another thing, an actor case representing the actor which performed or caused the movement, and a direction case indicating the start and end point of the movement. Often the start point of an EXPEL is a part of the body of the actor. If a surgeon removes a bullet, a tumor, or a parasite from another person's body, however, the surgeon is the actor, but the start point of the movement of the object is a body part of another individual.

- *GRASP*: The GRASP act primitive represents the event of a thing grasping or becoming attached to another thing. The GRASP act has an object case, representing the thing which is being GRASPed, and an actor case representing the actor which performed the GRASPing.

PTRANS and MOVE are very similar primitives because they both involve movement from one place to another: for PTRANS an entire thing moves, while for MOVE, an animate thing only moves part of its body. In building the reasonableness monitor prototype system, I found it difficult to find ConceptNet anchors allowing us to determine whether a verb should instantiate a PTRANS or MOVE. Because of this, I chose to combine the PTRANS and MOVE primitives into a single primitive, which I call MOVE-PTRANS, or simply MOVE. Any referral to MOVE in this thesis is the MOVE-PTRANS primitive.

Appendix B

Code

B.1 Vehicle Specific Artifacts

```
(define (make-bus-code-mapping #!optional mapping-file)
  (set! *bus-code-mapping* (make-strong-eq-hash-table))
  (hash-table/put! *bus-code-mapping* 22 'lateral)
  (hash-table/put! *bus-code-mapping* 23 'acceleration)
  (hash-table/put! *bus-code-mapping* 25 'steering)
  (hash-table/put! *bus-code-mapping* 30 'brakes)
  (hash-table/put! *bus-code-mapping* '3e 'gear-rotation)
  (hash-table/put! *bus-code-mapping* 'b1 'front-wheels)
  (hash-table/put! *bus-code-mapping* 'b3 'back-wheels)
  (hash-table/put! *bus-code-mapping* 'b4 'speed)
  (hash-table/put! *bus-code-mapping* 120 'drive-mode)
  (hash-table/put! *bus-code-mapping* 244 'gas-pedal)
  (hash-table/put! *bus-code-mapping* 'groundtruthxyz 'ground-truth)
  (hash-table/put! *bus-code-mapping* 'groundtruthheading 'heading))
```

Figure B-1: CAN bus mapping code for the vehicle simulation in Chapter 3

```
(define (isBraking? snapshot)
  (eqv? (log-snapshot-brake snapshot) 0))

(define (isAccelerating? snapshot)
  (eqv? (log-snapshot-accel snapshot) 'inc))

(define (isTurningRight? snapshot)
  (eqv? (log-snapshot-steering snapshot) 'inc))

(define (isTurningLeft? snapshot)
  (eqv? (log-snapshot-steering snapshot) 'dec))
```

Figure B-2: A subset of the edge detection rules for the “intervals of interest” in Chapter 3.

```
(define w) ;; width of the car in front from lidar sensor
(define k) ;; distance from the front wheel to self
(define l) ;; self's wheel base
(define r) ;; radius of self
(define d) ;; lenth of self

(define rlsqdiff (e:- (e:square r) (e:square l)))
(define lksumsq (e:square (e:+ l k)))
(define c (e:square (e:- (e:sqrt rlsqdiff) w)))
(define sqrtres (e:sqrt(e:-(e:+ rlsqdiff lksumsq) c)))

;;minimum space needed
(define m (e:+ d (e:- (e:- sqrtres l) k)))
(add-content w 2.43) ;;m
;;estimate based on l and d
(add-content k 0.8)
(add-content l 2.8804)
(add-content r 10.82)
(add-content d 4.8285)

(define distance-threshold m)
(define actual-distance) ;  read from processed log snapshot
```

Listing 13: Propagator code to calculate the minimum space needed to parallel park.

```
:safe_car_policy a air:Policy;
  air:rule :light-rule;
  air:rule :pedestrian-rule;
  air:rule :right-turn-rule;
  air:rule :speed-rule .

:pedestrian-rule a air:Belief-rule;
  air:if {
    foo:some_pedestrian
    ont1:InPathOf foo:my_car.
  };
  air:then [
    air:description ("Pedestrian detected");
    air:assert [air:statement{
        foo:my_car
        air:non-compliant-with
    :safe_car_policy .}]];
  air:else [
    air:description ("No obstructions");
    air:assert [air:statement{
        foo:my_car
        air:compliant-with
        :safe_car_policy .}]] .

:light-rule a air:Belief-rule;
  air:if { :EVENT a :V;
    ont1:Location
    foo:some_traffic_light.
};
  air:then [air:rule :traffic-light-rule].
```

Listing 14: A subset of the safe-driving rules written in AIR.

B.2 Adaptable Code Artifacts

These are independent code “snippets” that can be used in multiple domains.

B.2.1 Conceptual Dependency Parsing

```
tokens = annotation.split()
tree = rep.parse_with_regex(tokens)

IPython.core.display.display(tree)
all_annotations.append(annotation['caption'])

concepts = rep.get_concepts(tree)

(noun, noun_phrase, adjectives) = rep.get_noun_phrase(tree)
(verb, obj, context, phrase_dict) = rep.get_verbs(tree, True)
```

Listing 15: The parsing process that creates a CD primitive frame.

B.2.2 Commonsense Data Querying

```python
def find_anchor(concept_phrase, anchors):
    """
    Search for a specific anchor from a set of anchors
    """
    logging.debug("searching for an anchor point for %s" % concept_phrase)

    for anchor in anchors:
        if anchor in concept_phrase:
            logging.debug("anchor point %s is partof the concept phrase: %s"
                          % (anchor, concept_phrase))
            triple = [concept_phrase, 'IsA', anchor]
            return make_fact(triple, "direct search")

    for anchor in anchors:
        if type(concept_phrase) is list:
            concept = concept_phrase[-1]
        else:
            concept = concept_phrase
        return get_closest_anchor(concept, 'IsA', anchors)
```

```python
def get_closest_anchor(concept, relation, anchors):
    """
    Goes through all the relations and tries to find the closest one.
    If the anchor point is in the isA hierarchy at all, it
    """
    for anchor in anchors:
        logging.debug("Searching for an IsA link between %s and %s" \
                      % (concept, anchor))

        obj = requests.get(query_prefix + concept + rel_term + 'IsA' +\
                           limit_suffix).json()
        edges = obj['edges']
        if edges:
            for edge in edges:
                if check_IsA_relation(concept, anchor, edge):
                    triple = [concept, 'IsA', anchor]
                    return make_fact(triple, "ConceptNet IsA link")
        else:
            return "not found"  # TODO this needs a better message
    # If it is never found, make default object
    triple = [concept, 'IsA', default_anchor]
    return make_fact(triple, "Default anchor point")


def make_fact(triple, reason):
    """
    Makes a basic data fact base in pandas data
    """
    logging.debug("Making a new fact: %s with reason: %s" % (triple, reason))
    [subject, predicate, obj] = triple
    fact_term = "%s %s %s" % (subject, predicate, clean_phrase(obj))
    return [fact_term, reason]
```

B.3 Interpreting LiDAR data

```
def get_raw_lidar(sample):
    """
    Loads LIDAR data from binary numpy format.
    Data is stored as (x, y, z, intensity, ring index).
    """
    lidar_data = nusc.get('sample_data', sample['data']['LIDAR_TOP'])
    file_path = nuscenes_root+data_name+'/'+lidar_data['filename']
    scan = np.fromfile(file_path, dtype=np.float32)
    return scan

def with_ring(sample):
    """
    Retuns (x, y, z, intensity, ring index).
    """
    scan = get_raw_lidar(sample)
    points = scan.reshape((-1,5))
    print(np.shape(points))
    return points

def visualize_rings(rings, ring_nums):
    """
    takes in the rings and the ring numbers
    """
    fig = plt.figure()
    ax = fig.add_subplot(111, projection='3d')
    ax.set_xlabel('X')
    ax.set_ylabel('Y')
    ax.set_zlabel('Z')

    for ring in ring_nums:
        temp = rings[rings[:,RING_IND]==ring]
        x = temp[:,0]
        y = temp[:,1]
        z = temp[:,2]

        ax.scatter(x,y,z, marker='o')
    plt.show()
```

Listing 16: Visualization code for examining specified beams.

```
my_sample_token = my_scene['first_sample_token']
my_sample = nusc.get('sample', my_sample_token)

raw = get_raw_lidar(my_sample)
rings = with_ring(my_sample)

visualize_rings(rings, [4,5,8])
visualize_rings(rings, [1,10,20])
```

Listing 17: Minimal working code for the LiDAR point cloud ring visualization.

B.4 Synthesizer

```
passenger is safe at velocity V between s and t
    AND( OR( safe driving at velocity V during s and t
             AND( moving V at state s
                  t succeeds s
                  moving V at state t ) )
         OR( obj is not a threat between s and t
             AND( OR( obj not a threat at s
                      obj is not moving
                      obj is not located near
                      obj is not a large object )
                  OR( obj not a threat at t
                      obj is not moving
                      obj is not located near
                      obj is not a large object ) ) ) ) )
```

Listing 18: The implemented goal tree used for passenger safety in the explanation synthesizer. “safe transitions” and “threatening objects” have been expanded, as defined in Equation 7.1 and Equation 7.2.

Note that there are multiple `AND (OR (...)` statements in Figure 11. This due to my backward-chaining algorithm. These statements can also be simplified, but they are left for readability; so the reader can see where the rules are expanded. For example, in line 2 of Listing 11, “safe transitions”: `safe driving at velocity V during s and t` is met only if `AND( moving V at state s, t succeeds s, moving V at state t ) )`

B.5 Sample Results

B.5.1 NuScenes Examples

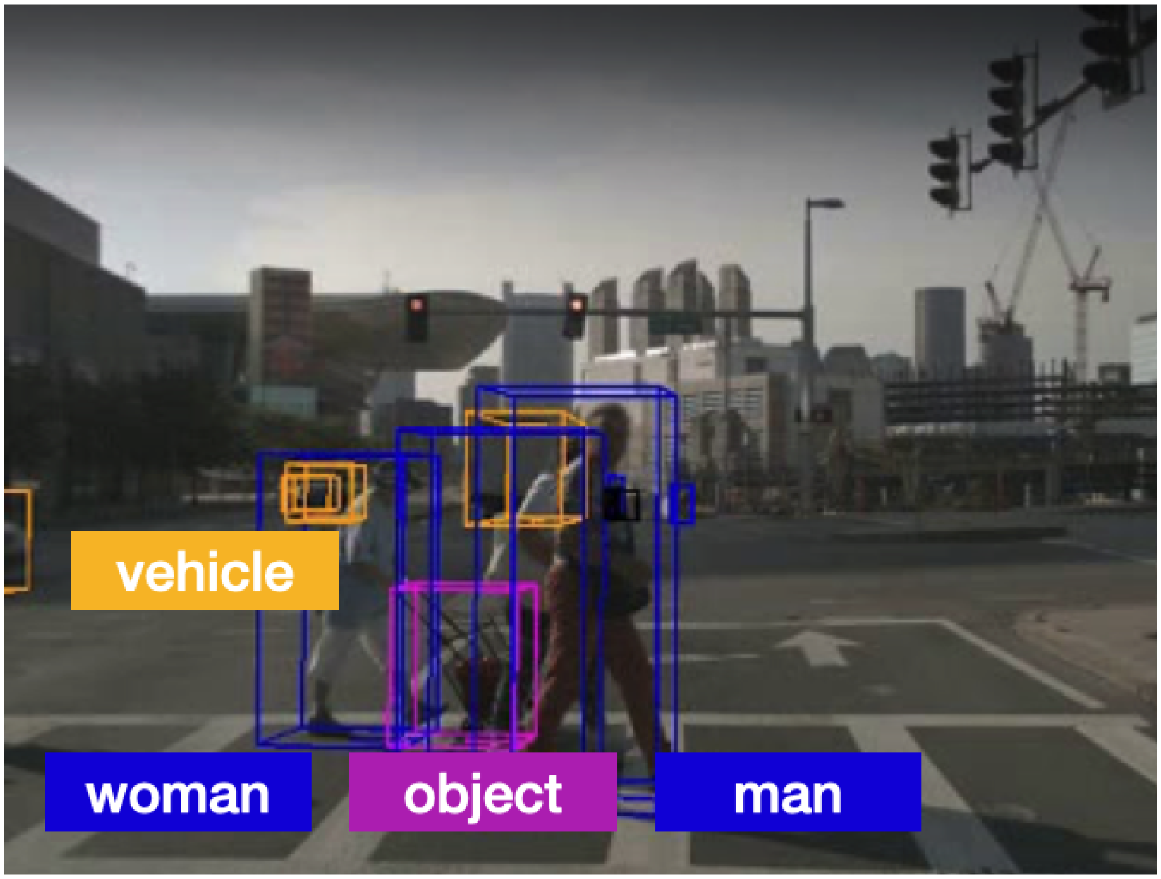


Figure B-3: A labeled data sample from NuScenes.

B.5.2 Parsing Examples

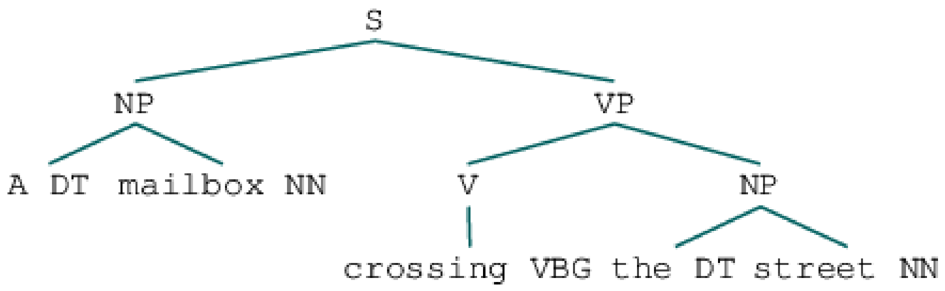


Figure B-4: The parse tree for "A mailbox crossing the street."

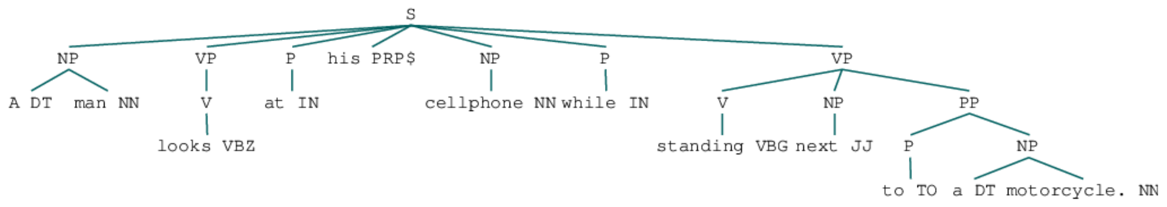


Figure B-5: The parse tree for a real image caption from "A man looks at his cellphone while standing next to a motorcycle."

```
@prefix foo: <http://foo#>.
@prefix car_ont: <http://car_ont#>.

foo:my_car
    a  car_ont:Vehicle ;
    car_ont:LastState "stop" ;
    car_ont:CurrentState "stop" ;
    car_ont:direction foo:some_traffic_light .

foo:some_pedestrians
    a car_ont:Pedestrian ;
    car_ont:label "woman" ;
    car_ont:CurrentState "move" ;
    car_ont:propel foo:woman-object ;
    car_ont:InPathOf foo:my_car .

    a car_ont:Pedestrian ;
    car_ont:label "man" ;
    car_ont:CurrentState "move" ;
    car_ont:NextTo foo:woman-object ;
    car_ont:InPathOf foo:my_car .

foo:woman-object
    a car_ont:Object ;
    car_ont:CurrentState "propel" ;
    car_ont:InPathOf foo:my_car .

foo:some_traffic_light
    a car_ont:TrafficLight ;
    car_ont:LightColor "red" .
```

Listing 19: The RDF log associated with Figure B-3.

```
import PyPDF2
from nltk.tokenize import word_tokenize

IF = 'if'
THEN = 'then'
BC = 'because'
RULE_KEYWORDS = [IF,THEN,BC]

def read_manual(file_name='MA_Drivers_Manual.pdf'):
    """
    File located at
    https://driving-tests.org/wp-content/uploads/2020/03/MA_Drivers_Manual.pdf
    """
    pdfFile = open(LOCAL_PATH+file_name, 'rb')
    # creating a pdf reader object
    pdfReader = PyPDF2.PdfFileReader(pdfFile)

    # printing number of pages in pdf file
    MAX_PAGES = pdfReader.numPages
    START_PAGE = 10 # The beginning few pages are indexes

    total_automatic = 0
    for page in range(START_PAGE, MAX_PAGES):
        pageObj = pdfReader.getPage(page)
        pageText = pageObj.extractText()
        total_automatic+=extract_if_then(pageText)

    # closing the pdf file object
    print("Found %d potential rules"%total_automatic)
    pdfFile.close()

def extract_if_then(page_text):
    """
    Check for rule keywords in text
    """
    if_counter = 0
    sentences = page_text.split('.')
    for sentence in sentences:
        tokens = word_tokenize(sentence.lower())
        if IF in tokens:
            words = [word for word in tokens if word.isalpha()]
            if_counter +=1
    return if_counter
```

Listing 20: Script for counting the number of probable rules in a driving manual.

Appendix C

Data Samples

C.1 LiDAR Data

Table C.1: A full, simulated Lidar trace.

N0	N0	N0	46.6	53.4	40	31.9	26.3	22.6	20	18
N0	N0	46.9	46.6	54.1	40.1	31.7	26.1	22.5	20	18
N0	N0	N0	79.6	54.6	40.1	31.6	25.9	22.5	20	18
N0	N0	N0	79.6	54.6	41.1	32.9	25.7	22.5	20	18
N0	N0	N0	79.5	54.7	41.1	32.7	26.3	23.1	20	18
N0	N0	N0	79.4	54.7	41.1	32.5	26.1	23	20.6	18.4
N0	N0	N0	79.3	54.7	41.1	32.5	26	22.9	20.6	18.4
N0	N0	N0	81.6	54.6	41.1	32.6	26	22.9	20.6	18.3
N0	N0	99.7	81.5	54.6	41.1	32.8	26.5	23	20.6	18.3
N0	N0	101.7	81.3	54.5	41	32.8	27	23.2	20.6	18.3
N0	N0	N0	81.1	54.4	41	32.8	27.2	23.4	20.6	18.3
N0	N0	N0	80.9	54.3	40.9	32.8	27.3	23.4	20.6	18.3
92.3	92.3	92.3	80.6	54.2	40.8	32.8	27.3	23.4	20.6	18.3
90.4	90.4	90.4	80.2	54	40.7	32.7	27.3	23.4	20.5	18.3
88.7	88.7	88.7	79.9	53.9	40.6	32.6	27.3	23.4	20.5	18.3
93.8	93.8	93.8	79.4	53.7	40.5	32.6	27.2	23.4	20.5	18.2

N0	N0	N0	79	53.5	40.4	32.5	27.2	23.3	20.5	18.2
N0	N0	N0	78.5	53.2	40.3	32.4	27.1	23.3	20.4	18.2
N0	N0	N0	78	53	40.2	32.3	27	23.3	20.4	18.2
N0	N0	N0	77.4	52.8	40	32.2	27	23.2	20.4	18.1
N0	N0	N0	76.8	52.5	39.8	32.1	26.9	23.1	20.3	18.1
N0	N0	N0	76.2	52.2	39.7	32	26.8	23.1	20.3	18.1
N0	N0	N0	75.6	51.9	39.5	31.9	26.8	23	20.2	18
N0	N0	N0	74.9	51.6	39.3	31.8	26.7	23	20.2	18
N0	N0	N0	74.2	51.3	39.1	31.7	26.6	22.9	20.1	18
N0	N0	N0	73.5	50.9	38.9	31.5	26.5	22.8	20.1	17.9
N0	N0	N0	72.8	50.6	38.7	31.4	26.4	22.8	20	17.9
N0	N0	N0	72.1	50.2	38.5	31.3	26.3	22.7	20	17.8
N0	N0	N0	71.4	49.9	38.3	31.1	26.2	22.6	19.9	17.8
N0	N0	N0	70.6	49.5	38.1	31	26.1	22.5	19.9	17.7
N0	N0	N0	69.8	49.1	37.9	30.8	26	22.5	19.8	17.7
N0	N0	118.6	69.1	48.7	37.7	30.7	25.9	22.4	19.7	17.6
N0	N0	116.3	68.3	48.4	37.4	30.5	25.8	22.3	19.7	17.6
N0	N0	114.1	67.5	48	37.2	30.4	25.7	22.2	19.6	17.5
N0	N0	111.9	66.8	47.6	37	30.2	25.6	22.1	19.5	17.5
N0	N0	109.8	66	47.2	36.7	30.1	25.4	22.1	19.5	17.4
N0	N0	107.6	65.2	46.8	36.5	29.9	25.3	22	19.4	17.4
N0	N0	105.6	64.5	46.4	36.2	29.7	25.2	21.9	19.3	17.3
N0	N0	103.5	63.7	46	36	29.6	25.1	21.8	19.3	17.3
N0	N0	101.6	62.9	45.6	35.8	29.4	25	21.7	19.2	17.2
N0	N0	99.6	62.2	45.2	35.5	29.2	24.9	21.6	19.1	17.2
N0	N0	97.7	61.5	44.8	35.3	29.1	24.7	21.5	19.1	17.1
N0	N0	95.9	60.7	44.4	35	28.9	24.6	21.4	19	17
N0	N0	94.1	60	44	34.8	28.8	24.5	21.3	18.9	17
N0	N0	92.4	59.3	43.7	34.5	28.6	24.4	21.3	18.8	16.9
N0	N0	90.7	58.6	43.3	34.3	28.4	24.3	21.2	18.8	16.9

N0	N0	89.1	57.9	42.9	34.1	28.3	24.1	21.1	18.7	16.8
N0	N0	87.5	57.2	42.5	33.8	28.1	24	21	18.6	16.8
N0	N0	85.9	56.6	42.2	33.6	27.9	23.9	20.9	18.6	16.7
N0	N0	84.4	55.9	41.8	33.4	27.8	23.8	20.8	18.5	16.6
N0	N0	83	55.3	41.4	33.2	27.6	23.7	20.7	18.4	16.6
N0	N0	81.6	54.7	41.1	32.9	27.5	23.6	20.6	18.4	16.5
N0	N0	80.3	54.1	40.8	32.7	27.3	23.5	20.5	18.3	16.5
N0	N0	79	53.5	40.4	32.5	27.2	23.3	20.5	18.2	16.4
N0	N0	77.7	52.9	40.1	32.3	27	23.2	20.4	18.1	16.4
N0	N0	76.5	52.3	39.8	32.1	26.9	23.1	20.3	18.1	16.3
N0	N0	75.4	51.8	39.4	31.9	26.7	23	20.2	18	16.3
N0	N0	74.2	51.3	39.1	31.7	26.6	22.9	20.1	18	16.2
N0	N0	73.2	50.7	38.8	31.5	26.4	22.8	20	17.9	16.1
N0	N0	72.1	50.2	38.5	31.3	26.3	22.7	20	17.8	16.1
N0	N0	71.1	49.7	38.3	31.1	26.2	22.6	19.9	17.8	16
N0	N0	70.2	49.3	38	30.9	26	22.5	19.8	17.7	16
N0	119	69.2	48.8	37.7	30.7	25.9	22.4	19.7	17.6	15.9
N0	116.5	68.4	48.4	37.4	30.5	25.8	22.3	19.7	17.6	15.9
N0	114	65.5	48	37.2	30.4	25.7	22.2	19.6	17.5	15.9
N0	111.7	64.6	47.5	36.9	30.2	25.5	22.1	19.5	17.5	15.8
N0	109.6	63.7	47.1	36.7	30	25.4	22	19.4	17.4	15.8
N0	107.5	63	46.4	36.5	29.9	25.2	21.8	19.3	17.3	15.7
N0	105.6	62.2	45.8	36.2	29.7	25.1	21.7	19.2	17.3	15.7
N0	103.8	61.3	45.4	35.4	29.6	25	21.6	19.2	17.2	15.6
N0	102.1	62.8	44.9	35.2	29.5	24.9	21.5	19.1	17.2	15.6
N0	100.5	62.1	44.6	35	28.5	24.9	21.5	19	17.2	15.6
N0	99	61.7	44.3	34.7	28.4	23.9	21.5	19	17.1	15.5
N0	97.6	61.4	44	34.6	28.3	23.9	21.5	19	17.1	15.5
N0	96.3	60.9	44.5	34.4	28.2	23.8	20.7	19	17	15.5
N0	95	60.4	44.2	34.2	28.2	23.8	20.7	18.9	17	15.4

N0	93.9	59.9	44	34.1	28.1	23.8	20.8	18.5	17	15.4
N0	92.8	59.5	43.7	34	28.1	23.8	20.8	18.5	16.6	15.4
N0	91.8	59	43.5	34.5	28.1	23.8	20.8	18.4	16.6	15.2
N0	90.8	58.6	43.3	34.3	28.1	23.8	20.9	18.4	16.6	15.2
N0	89.9	58.3	43.1	34.2	28.1	23.8	20.8	18.4	16.5	15.1
N0	89.1	57.9	42.9	34.1	28.1	23.8	20.7	18.3	16.5	15.1
N0	88.4	57.6	42.7	34	28.1	23.9	20.6	18.3	16.5	15.1
N0	87.7	57.3	42.6	33.9	28.1	23.7	20.6	18.3	16.5	15
N0	87.1	57.1	42.4	33.8	28.1	23.6	20.5	18.3	16.5	15
N0	86.5	56.8	42.3	33.7	28	23.5	20.5	18.2	16.5	15
N0	86	56.6	42.2	33.6	27.9	23.4	20.5	18.2	16.4	14.9
N0	85.6	56.4	42.1	33.6	27.9	23.4	20.4	18.1	16.3	14.9
N0	85.2	56.2	42	33.5	27.9	23.8	20.4	18.2	16.2	14.9
N0	84.8	56.1	41.9	33.4	27.8	23.8	20.3	18.1	16.2	14.8
N0	84.5	56	41.8	33.4	27.8	23.8	20.3	18	16.2	14.7
N0	84.3	55.9	41.8	33.4	27.8	23.8	20.3	17.9	16.1	14.6
N0	84.1	55.8	41.7	33.3	27.7	23.8	20.8	17.8	16	14.6
N0	84	55.7	41.7	33.3	27.7	23.8	20.8	17.8	15.9	14.5
N0	83.9	55.7	41.7	33.3	27.7	23.7	20.7	17.7	15.9	14.5
N0	83.9	55.7	41.7	33.3	27.7	23.7	20.7	17.6	15.8	14.4
N0	83.9	55.7	41.7	33.3	27.7	23.7	20.6	18.1	15.7	14.3
N0	83.9	55.7	41.7	33.3	27.7	23.7	20.5	18	15.6	14.2
N0	84.1	55.8	41.7	33.3	27.7	23.7	20.4	17.9	15.5	14.1
N0	84.2	55.8	41.7	33.3	27.8	23.7	20.4	17.8	16	14.1
N0	84.5	55.9	41.8	33.4	27.8	23.8	20.4	17.8	15.9	14
N0	84.7	56	41.9	33.4	27.8	23.8	20.4	17.7	15.8	14.4
N0	85	56.2	41.9	33.5	27.8	23.8	20.5	17.8	15.7	14.4
N0	85.4	56.3	42	33.5	27.9	23.9	20.7	17.8	15.6	14.3
N0	85.9	56.5	42.1	33.6	27.9	23.9	20.7	17.9	15.6	14.2
N0	86.3	56.7	42.3	33.7	28	23.9	20.8	17.9	15.5	14.2

N0	86.9	57	42.4	33.8	28	24	20.9	18.1	15.5	14.2
N0	87.5	57.2	42.5	33.8	28.1	24	21	18.2	15.6	14.3
N0	88.1	57.5	42.7	33.9	28.2	24.1	21	18.4	15.8	14.3
N0	88.9	57.8	42.9	34	28.2	24.1	21.1	18.5	16.1	14.4
N0	89.6	58.2	43	34.2	28.3	24.2	21.1	18.6	16.3	14.5
N0	90.5	58.5	43.2	34.3	28.4	24.2	21.2	18.7	16.5	14.6
N0	91.4	58.9	43.4	34.4	28.5	24.3	21.2	18.8	16.6	14.8
N0	92.4	59.3	43.7	34.6	28.6	24.4	21.3	18.8	16.7	14.9
N0	93.5	59.7	43.9	34.7	28.7	24.5	21.3	18.9	16.8	15.1
N0	94.6	60.2	44.1	34.9	28.8	24.5	21.4	18.9	16.9	15.2
N0	95.8	60.7	44.4	35	28.9	24.6	21.4	19	16.9	15.3
N0	97.1	61.2	44.7	35.2	29	24.7	21.5	19	17	15.4
N0	98.5	61.7	45	35.4	29.1	24.8	21.6	19.1	17.1	15.5
N0	99.9	62.3	45.3	35.6	29.3	24.9	21.6	19.1	17.2	15.6
N0	101.5	62.9	45.6	35.7	29.4	25	21.7	19.2	17.2	15.6
N0	103.2	63.6	45.9	36	29.5	25.1	21.8	19.3	17.3	15.6
N0	104.9	64.2	46.3	36.2	29.7	25.2	21.9	19.3	17.3	15.7
N0	106.8	64.9	46.6	36.4	29.8	25.3	21.9	19.4	17.4	15.7
N0	108.8	65.6	47	36.6	30	25.4	22	19.4	17.4	15.8
N0	110.9	66.4	47.4	36.9	30.1	25.5	22.1	19.5	17.5	15.8
N0	113.2	67.2	47.8	37.1	30.3	25.6	22.2	19.6	17.5	15.8
N0	115.5	68	48.2	37.3	30.5	25.7	22.3	19.6	17.6	15.9
N0	118.1	68.9	48.7	37.6	30.6	25.9	22.4	19.7	17.6	15.9
N0	N0	69.8	49.1	37.9	30.8	26	22.5	19.8	17.7	16
N0	N0	70.8	49.6	38.2	31	26.1	22.6	19.9	17.7	16
N0	N0	71.8	50.1	38.4	31.2	26.3	22.7	19.9	17.8	16.1
N0	N0	72.8	50.6	38.7	31.4	26.4	22.8	20	17.9	16.1
N0	N0	73.8	51.1	39	31.6	26.5	22.9	20.1	17.9	16.2
N0	N0	74.9	51.6	39.3	31.8	26.7	23	20.2	18	16.2
N0	N0	76.1	52.1	39.6	32	26.8	23.1	20.3	18.1	16.3

N0	N0	77.3	52.7	40	32.2	27	23.2	20.3	18.1	16.3
N0	N0	78.5	53.3	40.3	32.4	27.1	23.3	20.4	18.2	16.4
N0	N0	79.8	53.8	40.6	32.6	27.3	23.4	20.5	18.3	16.4
N0	N0	81.1	54.4	41	32.8	27.4	23.5	20.6	18.3	16.5
N0	N0	82.5	55.1	41.3	33.1	27.6	23.6	20.7	18.4	16.6
N0	N0	83.9	55.7	41.7	33.3	27.7	23.8	20.8	18.5	16.6
N0	N0	85.4	56.3	42	33.5	27.9	23.9	20.9	18.5	16.7
N0	N0	86.9	57	42.4	33.8	28	24	21	18.6	16.7
N0	N0	88.5	57.7	42.8	34	28.2	24.1	21	18.7	16.8
N0	N0	90.1	58.3	43.1	34.2	28.4	24.2	21.1	18.7	16.8
N0	N0	91.8	59	43.5	34.5	28.5	24.3	21.2	18.8	16.9
N0	N0	93.4	59.7	43.9	34.7	28.7	24.5	21.3	18.9	17
N0	N0	95.1	60.4	44.3	34.9	28.8	24.6	21.4	19	17
N0	N0	96.9	61.1	44.6	35.2	29	24.7	21.5	19	17.1
N0	N0	98.8	61.9	45	35.4	29.2	24.8	21.6	19.1	17.1
N0	N0	100.7	62.6	45.4	35.7	29.3	24.9	21.7	19.2	17.2
N0	N0	102.7	63.4	45.8	35.9	29.5	25	21.8	19.2	17.2
N0	N0	104.7	64.1	46.2	36.1	29.7	25.2	21.8	19.3	17.3
N0	N0	106.7	64.9	46.6	36.4	29.8	25.3	21.9	19.4	17.3
N0	N0	108.8	65.6	47	36.6	30	25.4	22	19.4	17.4
N0	N0	110.9	66.4	47.4	36.8	30.1	25.5	22.1	19.5	17.5
N0	N0	113.1	67.2	47.8	37.1	30.3	25.6	22.2	19.6	17.5
N0	N0	115.3	67.9	48.2	37.3	30.5	25.7	22.3	19.6	17.6
N0	N0	117.5	68.7	48.6	37.5	30.6	25.8	22.4	19.7	17.6
N0	N0	119.7	69.5	48.9	37.8	30.8	25.9	22.4	19.8	17.7
N0	N0	N0	70.2	49.3	38	30.9	26	22.5	19.8	17.7
N0	N0	N0	71	49.7	38.2	31.1	26.2	22.6	19.9	17.8
N0	N0	N0	71.7	50	38.4	31.2	26.3	22.7	19.9	17.8
N0	N0	N0	72.5	50.4	38.6	31.3	26.3	22.7	20	17.8
N0	N0	N0	73.2	50.7	38.8	31.5	26.4	22.8	20	17.9

N0	N0	N0	73.9	51.1	39	31.6	26.5	22.9	20.1	17.9
N0	N0	N0	74.6	51.4	39.2	31.7	26.6	22.9	20.2	18
N0	N0	N0	75.2	51.7	39.4	31.8	26.7	23	20.2	18
N0	N0	N0	75.9	52	39.6	31.9	26.8	23.1	20.2	17.8
N0	N0	N0	76.5	52.3	39.8	32.1	26.9	23.1	20.1	17.8
N0	N0	N0	77.1	52.6	39.9	32.2	26.9	23.2	20.1	17.8
N0	N0	N0	77.6	52.9	40.1	32.3	27	23.2	20.1	17.9
N0	N0	N0	78.2	52.8	40.2	32.4	27.1	23.3	20.1	17.9
N0	N0	N0	78.7	52.4	40.3	32.4	27.1	23.3	20.1	17.9
N0	N0	N0	79.1	51.6	40.5	32.4	27.2	23.2	20.1	17.9
N0	N0	N0	79.6	52.1	39.5	32.3	27.1	23.1	20.1	17.9
N0	N0	N0	80	51.2	39.7	32.2	26.9	23	20	17.9
N0	N0	N0	80.3	52	39.8	32.1	26.7	22.9	20	18
N0	N0	N0	80.6	52.8	39.8	32	26.5	22.8	20	18

```
lidar N0 N0 N0 046.62432 053.44825 039.97103 031.9073 026.28929
022.64947 020.04059 017.98683 N0 N0 046.87839 046.64302 054.0672
040.0536 031.74601 026.07668 022.54086 020.03818 017.99744 N0 N0
N0 079.60463 054.57677 040.13287 031.59498 025.86347 022.4957
020.03653 018.00723 N0 N0 N0 079.56297 054.63397 041.07882
032.86723 025.65002 022.45222 020.03563 018.01616 N0 N0 N0
079.47211 054.66991 041.09912 032.67908 026.32562 023.054
020.03549 018.02423 N0 N0 N0 079.38465 054.68449 041.10737
032.47697 026.14731 022.98088 020.60007 018.35239 N0 N0 N0
079.33179 054.67776 041.10355 032.4968 025.97624 022.91073
020.59906 018.35169 N0 N0 N0 081.58467 054.64955 041.08763 032.63
025.96671 022.88974 020.60324 018.34851 N0 N0 099.73756 081.47443
054.60002 041.05967 032.77287 026.51481 023.02333 020.60772
018.34291 N0 N0 0101.6534 081.31727 054.52946 041.01976 032.80005
026.98192 023.20032 020.6072 018.33497 N0 N0 N0 081.11401
054.43799 040.96796 032.81677 027.19497 023.3803 020.59934
018.32467 N0 N0 N0 080.86557 054.32598 040.90452 032.80289
027.33922 023.42793 020.58329 018.312 092.31916 092.31704
092.32194 080.57301 054.19383 040.82962 032.75472 027.34817
023.43776 020.56436 018.297 090.39896 090.397 090.40192 080.23775
054.04201 040.74336 032.69921 027.30945 023.44469 020.54245
018.2797 088.66282 088.66101 088.66593 079.86122 053.87103
040.6461 032.63658 027.26583 023.41444 020.51785 018.26018
093.79497 093.78721 093.78659 079.44511 053.6814 040.53813
032.56696 027.21724 023.37859 020.49034 018.23841 N0 N0 N0
078.99117 053.4738 040.41964 032.49045 027.16378 023.33926
020.46006 018.21449 N0 N0 N0 078.50139 053.24896
```

Figure C-1: A sample of the simulated LiDAR data extracted from a simulated vehicle log. This corresponds to a subset of a single snapshot (or point in time).

		`LidarPointCloud` instance			
		x	y	z	intensity
Ring Index	0	-3.12	-0.43	-1.87	4.00
	1	-3.29	-0.43	-1.86	1.00
	2	-3.47	-0.43	-1.86	2.00
	3	-3.67	-0.43	-1.86	3.00
	4	-3.9	-0.43	-1.86	6.00
	5	-4.17	-0.42	-1.87	5.00
	6	-4.43	-0.42	-1.86	7.00
	7	-4.75	-0.42	-1.87	22.00
	8	-5.04	-0.41	-1.85	12.00
	9	-5.04	-0.41	-1.72	6.00
	10	-5.41	-0.41	-1.7	45.00
	11	-5.85	-0.4	-1.69	29.00
	12	-6.33	-0.4	-1.67	30.00
	13	-6.84	-0.39	-1.63	35.00
	14	-7.36	-0.38	-1.58	41.00
	15	-8.21	-0.37	-1.56	44.00
	16	-5.49	-0.42	-0.92	31.00
	17	-10.51	-0.4	-1.49	22.00
	18	-11.5	-0.39	-1.36	5.00
	19	-13.62	-0.37	-1.29	5.00
	20	-16.54	-0.35	-1.17	2.00
	21	-22.	-0.31	-1.04	9.00
	22	-21.73	-0.3	-0.52	26.00
	23	-2.17×10	-3.00×10^{-1}	-1.00×10^{-2}	4.30×10
	24	0.	-4.50×10^{-1}	-1.0×10^{-2}	3.00
	25	-14.22	-0.34	0.65	6.00
	26	0	-4.50×10^{-1}	-1.00×10^{-2}	1.14×10^{2}
	27	-14.16	-0.34	1.31	88.00
	28	-14.17	-0.33	1.64	85.00
	29	-14.14	-0.33	1.97	81.00
	30	-14.14	-0.33	2.31	75.00
	31	-14.12	-0.32	2.65	40.00

Table C.2: A raw data table of a subset of the NuScenes LiDAR traces.

C.2 Simulations

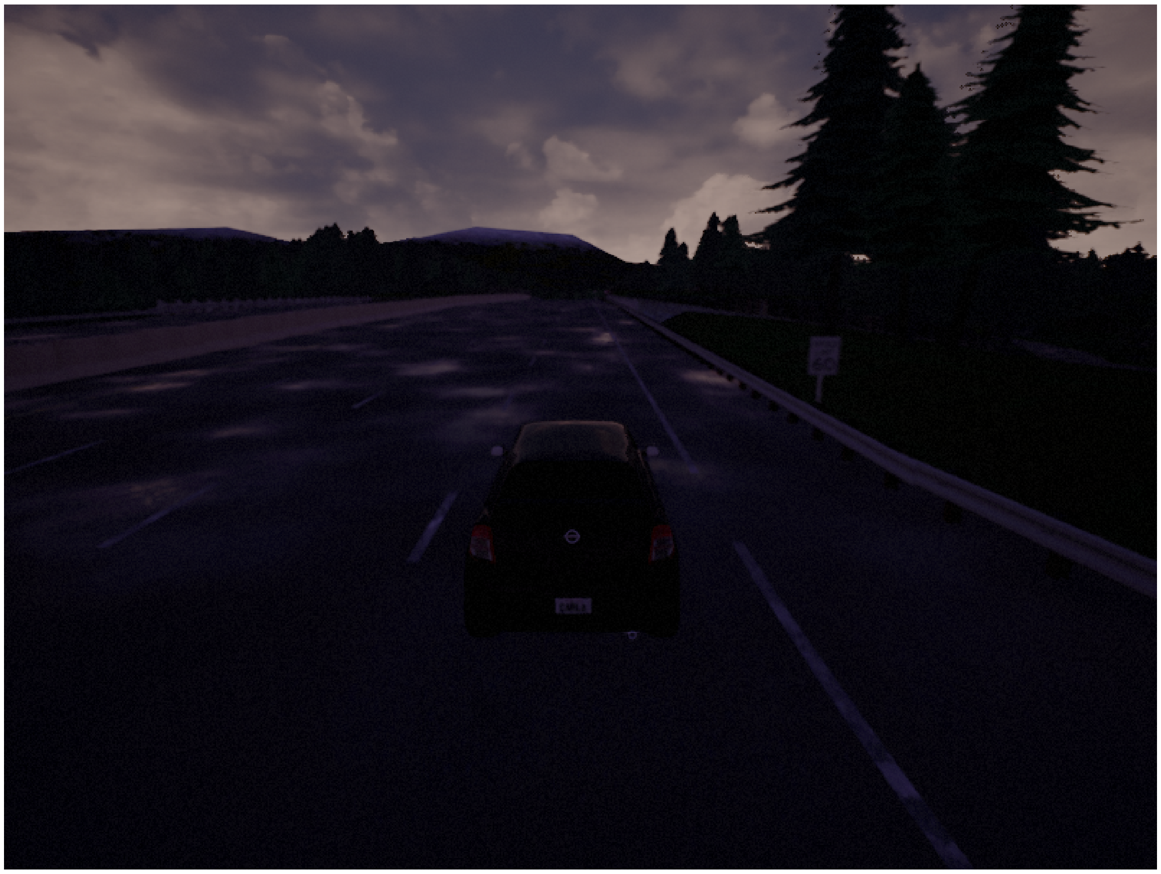


Figure C-2: A screenshot of the Uber accident simulation (with similar lighting to the report) on the Carla Platform.

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