THE NEXT GREAT AI

APPROACH TO DETECTING BEHAVIORAL ANOMALY IN AUTONOMOUS DRIVING

ASSIGNMENT – 5

IFT 598 – AI IN CYBER SECURITY

Arizona State University

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Abstract:

Problem statement - According to a recent report from a US car-safety agency, roughly 400 crashes involving cars with partially automated driver assistance systems were recorded by US automakers.

There are now significant advances toward a future with driverless vehicles on our roads. While autonomous cars appear to function well under controlled settings, they fail to deal with the unexpected, and their potential to decrease traffic accidents remains unrivaled. This research tackles this issue and presents a unique method of evaluating AV accident risks by comparing them to a more recognized and measurable risk - human behavior [1].

This approach is used to measure AV safety in comparison to human drivers in advance. Currently, abnormal driving behavior is caused by human vulnerabilities such as weariness or aggressiveness. To compare human and AV driving behaviors, an Artificial Intelligence model AV is simulated using Convolutional Neural Networks (CNN). Contextual driving abnormalities are recognized using a machine learning approach called Gaussian Processes (GP), the frequency and severity of which are used to calculate a risk score. This study provides a starting point for tackling the problems associated with AV risk modeling.

Introduction:

Anomalies, also known as corner cases, occur on the street on a daily basis, which is why autonomous cars must deal with them. Many regard the "long tail of unusual occurrences" [as the primary impediment to large-scale deployments of autonomous cars . While there have been promising developments in dealing with the unusual and unknown , it remains critical to discover abnormalities, which is still difficult [2].

Currently, AVs do not meet human safety standards. One of the most critical issues for automakers, insurers, and legislators is quantifying the risks. The capacity to objectively compare the safety of AVs to human drivers is very important. Traditional risk frameworks are currently hampered by a lack of historical data, experience, and the inherent difficulties of autonomous technology.

The goal of this study is to provide a proactive and unique framework for comparing AV risks to human drivers, therefore facilitating their safe and timely deployment. The acceptability and public adoption of AVs is predicated on the assumption that they will be far safer than humans. As a result, the safety of human drivers is an important criterion for assessing the performance of AVs. However, it is practically hard to draw statistically significant comparisons without accumulating hundreds of millions of autonomous kilometers [3]. According to Fraade-Blanar et al. [4] "leading metrics" such as cumulative mileage, disengagements, driving offences, and behavior should be used. In essence, crash antecedent characteristics that connect with AV accidents, providing a more sophisticated approach. Safety-critical occurrences or crash precedents serve as surrogate risk metrics for people [5], [6]. These occurrences usually occur when the vehicle exceeds a threshold that deviates from "normal driving," such as lateral and longitudinal acceleration. Although AVs are less vulnerable to such human tendencies, the risk of driving will not be removed.

Vulnerabilities in software, hardware, cyber, and human-machine interaction will emerge as technological threats.

Approach:

A statistical anomaly detection tool for autonomous driving that uses deviations from normal human driving as a proxy baseline measure of risk. This has several advantages.

- It allows for statistically significant comparisons between humans and AVs.
- In contrast to AV data, human driving data is easily accessible via telematics and insurance firms.

A novel methodology is given for detecting geographical abnormalities in driving behaviors utilizing AI approaches such as Bayesian Machine Learning (ML) and a geostatistical tool known as Gaussian Processes (GP). GPs are used to imitate typical driving behavior in a virtual setting using six human drivers. Normal driving habits are specifically modelled for each road segment across three simulated tracks, allowing us to statistically identify spatial abnormalities for both human and AV. To comparison, we simulate an AV model using Convolutional Neural Networks (CNNs). CNNs are taught to predict steering angle and velocity based on picture inputs. The suggested technique has several advantages.

Bayesian Machine Learning(ML) [7]:

Bayesian ML is a statistical modeling approach based on Bayes' Theorem.

$p(\theta|x)=p(x|\theta)p(\theta)p(x)$

In general, Bayesian ML seeks to estimate the posterior distribution ($p(\theta|x)p(|\theta|x)$) given the likelihood ($p(x|\theta)p(x|\theta)$) and the prior distribution, $p(\theta)p(\theta)$. The probability may be determined based on the training data.

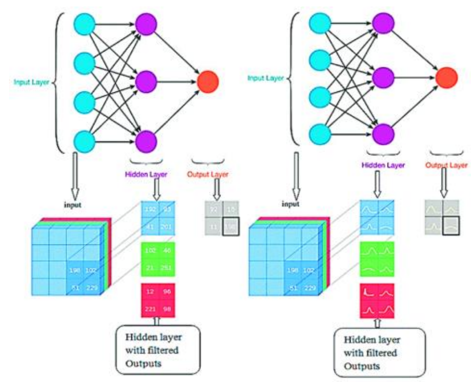

Fig1: Bayesian Machine Learning

Gaussian Processes (GP) [8]:

A Gaussian process is a stochastic process (a collection of random variables indexed by time or space) in probability theory and statistics in which every finite collection of those random variables has a multivariate normal distribution, i.e., every finite linear combination of them is normally distributed. A Gaussian process's distribution is the sum of all those (infinitely numerous) random variables, and as such, it is a distribution over functions having a continuous domain, such as time or space.

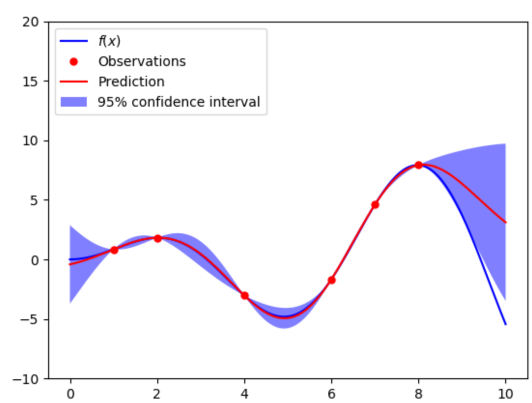

Fig2: Gaussian Processes

Convolutional Neural Networks(CNN) [9]:

A Convolutional Neural Network (CNN) is made up of one or more convolutional layers (sometimes with a subsampling step) followed by one or more fully connected layers, just like a traditional multilayer neural network. A CNN's architecture is intended to take use of the 2D structure of an input picture (or other 2D input such as a speech signal). This is accomplished using local connections and linked weights, followed by some type of pooling, resulting in translation invariant characteristics. CNNs are also easier to train and have many fewer parameters than fully linked networks with the same number of hidden units.

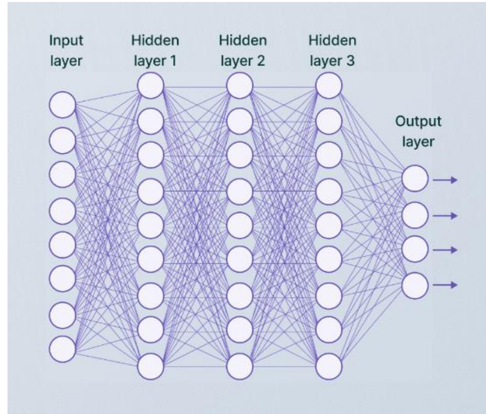

Fig1: Convolutional Neural Networks

Anomaly Detection:

Setting a threshold at which a safety-critical driving event occurs is the most prevalent way to anomaly detection. Anomaly driving, on the other hand, is spatially dependent. For example, forceful braking on highways vs city streets, or swerving right on a road segment that veers left. As a result, similar driving occurrences are unusual depending on location and driving environment. The suggested technique for detecting GP anomalies combines geographical modeling and statistical anomaly identification.

Workflow:

In this part, we will look at autonomous driving methods as well as current research in the subject of AV safety and risk.

- Safety and Driving Risk
- Autonomous Driving

The great majority of traffic accidents are caused by poor driving habits. Abnormal driving behaviors include weaving, swerving, turning, and rapid braking, among other things. A driver's behaviors might represent a variety of various behavioral states, including normal, inebriated, fatigued, and irresponsible. The association between driving behavior and collision incidence has been extensively studied. It is also known as safety-critical event analysis, dangerous driving, atypical driving, near collisions, or near misses.

Anomaly, outlier, or novelty identification is the process of finding unusual occurrences in machine learning. The goal is to discern between aberrant and typical driving behaviors, and numerous anomaly detection approaches have been presented in the context of manually driven automobiles, including as

- A rule-based approach.
- Multivariate Normal anomaly detection.
- Support vector machines.

- fuzzy logic approach.
- **GPs** have been used in my technique for a variety of anomaly detection applications, including marine vessel behavior.

Real-world or simulation testing can be used to evaluate the performance and safety of AVs. Vehicle-level or real-world testing is the most statistically meaningful technique since the AV functions in real-world driving situations and interacts with real road users . Simulation testing is an alternate and successful method for assessing the safety of AVs and estimating their dangers. Model-based simulations, such as Carla and AirSim , are a valuable technique because they may include a greater range of driving circumstances in settings that may not be easily available with real-world testing.

In general, there are two methods to autonomous driving that differ in terms of modularity or the number of subcomponents.

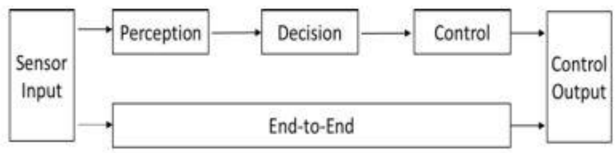

Fig4: Two methods to autonomous driving

Data Collection & Methodology:

A simulation track generates and collects data. Driving data was gathered for two reasons: training the GP and CNNs. To begin, a group of male drivers was employed to simulate natural human driving. Each driver was instructed to navigate each track safely using a handheld controller. Each human driver's saved two journeys will be utilized to mimic typical driving behavior. Steering angles and velocities are gathered and stored for each driver at each unique road section in order to train the GP.

In the actual world, this would be readily available through insurance and telemetry businesses. To break each test track into separate granular road segments, k-means clustering is used. To simulate an AV model, we need to create around 1 hour of data to be used in the training of two CNNs. The authors developed and gathered training data for this, which varies from data collected from research participants.

The simulated vehicle should have at least three front-facing cameras capable of producing roughly 30 photos per second. These pictures, together with their related control commands (velocity and steering angle), are utilized to train two CNNs, one for velocity prediction and the other for steering angle prediction, using images as inputs. The steering angles are measured in degrees, with the left and right angles being positive and negative, respectively.

Most vehicle accidents involve two or more cars, and interactions between vehicles contribute significantly to the complexity of driving. This will become increasingly critical when blended or mixed autonomous settings evolve.

An AV is taught to anticipate steering angles and velocity and to navigate without human involvement using Convolutional Neural Networks.

The GPs may be modeled using GPy, an open source Gaussian Process framework written in Python and developed by the Sheffield machine learning group. The approach is separated into two parts.

- Anomaly Detection Using Gaussian Processes (GP)
- Convolutional Neural Networks (CNNs) (CNN)

Using GP Anamoly detection, we can model typical driving patterns based on human driving and statistically identify outliers based on the model AV's driving behavior. To do this, we use GPs to model typical human-based driving and statistically identify abnormalities based on the likelihood of witnessing sensor readings.

The GP anomaly detection and risk scoring technique assesses risk for both humans and automated vehicles based on the frequency and severity of safety-critical or anomalous driving occurrences, independent of the underlying risk. The severity of abnormalities is determined after they have been found. Anomalies can vary from minor deviations to near-misses and crashes. In terms of steering irregularities, the car may veer slightly towards the road edge or totally cross lane lines. Finally, localizing occurrences and mapping locations with severity levels. Identifying high-risk road portions can provide a more thorough risk profile for the AV.

CNNs are comparable to deep neural networks in that they consist of a series of layers made up of neurons. Convolutional layers, on the other hand, are organized in three dimensions: height, breadth, and depth. Our CNN weights are trained to reduce the squared error between the network's projected steering angle and velocity instructions and the human driver's command output. In essence, each image created by the human driver is accompanied by a steering and velocity order. The network is then taught to reproduce the shown behavior as closely as feasible.

Conclusion:

Using this method, we may see a lot of aberrant behaviors that were correctly recognized by the GP anomaly detection model. This strategy demands better coordination between automakers and policyholders, who have the essential human driving data and quantitative risk models. This will makes an important contribution to methodologies for evaluating the risk of AV driving. It is a critical duty, not only for the advancement of research, but also for assuring society acceptance and faith in this new technology.

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