Driving Styles Classification on Highway

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10672224 : Artificial Intelligence Basics

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# Abstract

Each driver differs from the other in the style of driving, and, of course, this style of driving affects road safety. In these studies, new methods of intelligent machine learning have been found based on data that can classify driving behavior. In some of these studies that were conducted, we searched for several driving behaviors, and we found different driving behaviors for each driver, and we used a data set from the driving simulation mechanism in order to know how to drive. An algorithm called the K-clustering algorithm was used with a method that was used as unsupervised machine learning to cluster driving behavior into classes (normal and aggressive).

This scenario-based testing is for the security approval of profoundly robotized vehicles. We propose an unused strategy of information estimation from an ethereal point of view for scenario-based confirmation that fulfills the prerequisites, and a broad normal vehicle direction information set from German rways, high D, was used to examine the vehicle following behavior of person drivers. This information incorporates the tracks of 110,000 vehicles recorded for 16.5 hours.

By minimizing differences between observed and recreated holes when following the portrayed lead vehicle, We analyzed the increasing speed chronology of characteristic and manufactured high-altitude drivers by utilizing recreations of two vehicle following models. An unused aggregate scale, corresponding to the vitality of the time-series bend of the subordinate position, was calculated for both the characteristic and modeled drivers. Human drivers had higher control and appeared to have more variance in increasing speed, some of the time carrying on nonsensically.

Keywords:Driving Behavior, Driving Style, Volatility Measures,K-mean clustering.

# Introduction

Driver behavior is the unintentional and intentional actions and characteristics a driver pulls off while operating a vehicle. There are many factors that can alter or contribute to a driver’s behavior, such as gender, attitude, experience, age, emotions, driving conditions, drowsiness, fatigue, etc. These external and internal factors can affect even the same driver’s ability to value risk and make decisions. Driver behaviors are frequently portrayed as normal. [3] Conservative and aggressive Several tools and techniques may be used to collect data about driving behavior. According to a study, among 120 selected studies from 2010 to 2020 in several resources, IoT sensors and in-vehicles played the greatest role in collecting data in around 67% of the selected studies. And of the types of data acquired, the most widely collected were those relating to vesicles. This study answers the question about the different data types and sources used by researchers. However, more studies are required to provide more attention to the driver’s data and to look over the data from three dimensions of driving together as an interconnected and integrated system [4].

In this paper, we used the traffic-flow-based dataset, which focuses on a particular scene and synchronously captures all the vehicles within it. This type of dataset uses a bird’s eye view to detect vehicle directions within the scene. The NGMS is the best dataset known that includes highway scenarios. Last year, RWTH Aachen University released the highD dataset, which used advanced computer vision technology to update the collection of data mechanisms based on the NGSIM dataset [5].

Recognizing and analyzing driving behavior has many benefits. For example, driving behavior can be connected with driving assistant systems as it can notify and alert the drivers that they are adopting an aggressive driving style [6]. Furthermore, driving behavior style recognition can be very useful in fuel consumption evaluation on the highway [7]. Moreover, insurance companies find it important to classify their driver’s behavior to know what premium accounts suit him.

So the question our research is willing to answer is how many possible driver behaviors are on the highway, and how to decide which behavior does a driver have using the thirteen volatility measure.

# Literature Review

**Learning to Drive from Observations while Staying Safe [10]**

aims to combine imitation learning methods like GAIL [11] with a rule-based safety framework to avoid collisions during training and testing. Our method is evaluated on highway driving scenes where all vehicles are controlled by our driving policies trained on the real-world driving dataset highD.

This would enable an AV policy [12] to be trained and tested on how to interact with human-driven vehicles.

**Vehicle Trajectory Prediction in Crowded Highway Scenarios Using Bird Eye View Representations and CNNs [13]**

A deep learning-based methodology has been trained using the HighD dataset, which contains vehicles' detection in a highway scenario from aerial imagery. The model has been tested in highway scenarios with more than 30 vehicles simultaneously in two opposite traffic flow streams, showing good qualitative and quantitative results. Highways are among the most common driving scenarios in which autonomous vehicles are starting to develop their autonomous capabilities.

**Learning Risk Level Set Parameters from Data Sets for Safer Driving [14]**

The data sets are used to improve vehicle safety and minimize the risks to a driver. Some of the factors that affect a driver's risk include time of day, location, and environmental factors. We can use risk level sets to analyze the data and derive relevant parameters for risk analysis.

We use the high-quality data sets of the NGSIM and the high-D to improve the vehicle’s safety and minimize the risks to a driver. One challenge in analyzing the data is understanding how to extract the relevant information from it. We can use risk level sets to analyze human driving data.

**Exploration of lane-changing duration for heavy vehicles and passenger cars: a survival analysis approach [15]**

The LC duration (LCD) measures the total time it takes for a vehicle to travel from the current lane to the target lane, which is an indispensable indicator to characterize the LC behavior. The aim is to further explore the LCD between heavy vehicles and passenger cars. LC trajectories are extracted from the newly-released high-D dataset. The LC maneuver is also very common in real traffic environments. The impact of the LC maneuver on traffic flow is more pronounced than that of the CF maneuver.

**Identification of Challenging Highway-Scenarios for the Safety Validation of Automated Vehicles Based on Real Driving Data [16]**

automated vehicles. Proof of their safety is essential to make people deal with it, but the problem of proof of safety is unsolved because many things can occur in different situations. With the scenario-based approach, it finds particularly challenging scenarios from real driving data and assesses their difficulty.

It is independent of the performance of the test vehicle and therefore valid for all Avs. The aim is to have a scenario catalog or database with scenarios that contains all "good" test cases for the safety assessment.

**Trajectory Prediction Based on Planning Method Considering Collision Risk [17]**

In Autonomous Vehicles, by using Anticipating the Trajectory, it will improve the AV's driving safety.In trajectory forecasting, the long-short-term memory (LSTM) network for sequential data has achieved great success in its planning-based methods following a sense-reason-predict scheme in which agents reason about intentions and possible ways to the goal. In addition, the collision risk is considered, and the most appropriate future trajectory will be selected based on the current state of the agent.

The planning-based method improves prediction accuracy compared with the baselines.We expect autonomous vehicles to improve driving safety by reducing the number of road accidents. Researchers began to focus on anticipating their future behavior to reach the level of human drivers like motion or trajectory.

**Graph Neural Network-based Clustering Enhancement in VANET for Cooperative Driving [18]**

There has been a development in the automobile industry, and the number of cars is increasing day by day. Accordingly, problems have increased, including traffic problems, accidents, environmental problems, and environmental damage, so we have created a driving method that reduces these problems. We use a Graph Neural Network (GNN) model to learn effective node representations.

It has been proved that platooning/clustering-based driving can significantly reduce road congestion and exhaust emissions and improve road capacity and energy efficiency, this paper aims to improve the stability of vehicle clustering to enhance the lifetime of cooperative driving, our centralized approach makes full use of the ubiquitous presence of the base stations and edge clouds, we evaluated the performance of the proposed clustering algorithms on the open-source highD dataset. The experiment results demonstrate that the average cluster lifetime and cluster efficiency of our GNN-based clustering algorithm outperform state-of-the-art baselines.

**Learning game-theoretic models of multiagent trajectories using implicit layers [19]**

We take a step towards addressing multiagent trajectory prediction by trying to keep as much as possible of the practical strength of data-driven approaches. For this, we hybridize neural learning with game-theoretic reasoning—because game theory provides well-established explanations of agents' behavior based on the principle of instrumental rationality. In experiments, we evaluate our approach on two real-world sets, where we predict highway drivers' merging trajectories and on a simple decision-making transfer task.

It uses a net that reveals preferences from the past joint trajectory and an implicit layer that maps these to local Nash equilibria. For tractability, we introduce a new class of continuous potential games and an equilibrium-separating partition of the action space. But it remains a challenge to use them for safety-critical domains with additional verification and decision-making transfer requirements, like automated driving or mobile robots in interaction with humans.

We consider this work as one step towards machine learning methods for this task that are more interpretable, verifiable, and transferable to decision making. A major challenge is making game-theoretic concepts tractable for such settings. Potential for future work lies in relaxing subspace-wise concavity, common-coupled games, and related assumptions.

**Interpretable Feature Generation using Deep Neural Networks and its Application to Lane Change Detection [20]**

The validation of deep learning architectures is considered one of the most crucial aspects when it comes to safety-relevant applications. The input data to be processed has to be transparent.

A vehicle should be able to predict the intention of other moving objects to perform a lane change maneuver. When the prediction is performed adequately, responses such as braking or lane changing can be initiated smoothly and comfortably.

**Computation-Aware Data-Driven Model Discrimination with Application to Driver Intent Identification [21]**

In most driving scenarios, model detection and identification play an important role in safety validation and assurance such that potential changes in other vehicles' system behaviors can be quickly detected. Many algorithms have been added to vehicles to improve their performance, such as: Gaussian process regression was used to estimate driver actions, and most learning-based Most of these algorithms do not analyze the modeling errors that might lead to failure, such as collision avoidance.

**The safety validation of highly automated vehicles [22]**

The performance of algorithms and systems in highly automated vehicles (HAV) is steadily increasing. However, the safety validation of HAVs remains an open issue. Existing methods, such as extensive test drives on public roads and reproducible tests on test tracks, are not feasible. The validation effort typically increases with the amount and complexity of the scenarios a system has to handle. The aforementioned ordinary methods are unfeasible because of cost and time commitment. Our proposed methods use real trajectories from the HD dataset to train neural networks that generate synthetic trajectories from intuitive parameters as input. At the same time, the neural networks can perform the inverse mapping from given trajectories to corresponding parameter values.

**Situation understanding in autonomous cars [23]**

Through years of practice, we have developed an intuitive ability to "see" a little further into the future and predict the movement of surrounding objects in complex real-world scenarios. Using the same approach, an autonomous car must be able to understand and predict the behavior of surrounding vehicles. Although humans are difficult to model, better analysis of human behavior should allow scientists to develop systems capable of making more "human-like" decisions.

Additionally, as human drivers can adopt different driving styles, the diversity of possible behaviors is almost endless. When driving on a highway, We present a new concept to classify and predict surrounding vehicle maneuvers on highways using Deep Neural Networks (DNN).

This paper also illustrates how this concept can be applied to real-world data gathered in the HighD project. The proposed approach consists of dividing the lane change maneuver into three stages: preparation, insertion, and adjustment, and identifying each stage by using a DNN-based model. The model is trained and tested using the HighD dataset. It shows satisfactory performance in classification and anticipation of lane changes.

# Dataset

The highD dataset is a new dataset of naturalistic vehicle trajectories recorded on German highways. Using a drone, typical limitations of established traffic data collection methods such as occlusions are overcome by the aerial perspective. Traffic was recorded at six different locations and included more than 110,500 vehicles. Each vehicle's trajectory, including vehicle type, size, and maneuvers, is automatically extracted. Using state-of-the-art computer vision algorithms, the positioning error is typically less than ten centimeters. Although the dataset was created for the safety validation of highly automated vehicles, it is also suitable for many other tasks, such as the analysis of traffic patterns or the parameterization of driver models.

The highD dataset includes data extracted from 60 recordings. For each recording, a total of four files are provided: an image of the recorded highway section, a csv file describing the recording location, another csv file containing an overview of recorded vehicle tracks, and a csv file for the tracks' trajectories. These files are created for each recording to ensure easy handling of the data. In the following, the dataset format and especially the meaning of every column are explained in detail.

|  |  |  |
| --- | --- | --- |
| **id** | **xVelocity** | **xAcceleration** |
| 1 | 40.85 | 0.3 |
| 1 | 40.87 | 0.3 |
| 1 | 40.88 | 0.31 |
| 1 | 40.89 | 0.32 |

xx\_tracks.csv

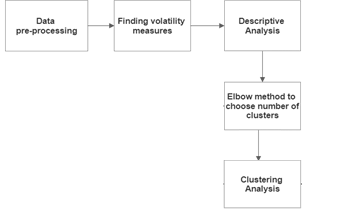
|  |  |
| --- | --- |
| **id** | **class** |
| 1 | Car |
| 2 | Car |
| 3 | Truck |
| 4 | Car |
| 5 | Car |
| 6 | Truck |

xx\_tracksMeta.csv

# Methods

The main contribution of this study is to classify the drivers behavior at highway roads.In total, we read the given data , and we used the given Volatility Measures for every driver to use it in classify operation , We applied volatility measures to understand driving behavior and actions in different situations , To classify driving behavior, the volatility measures were used as the input

To know the driver behavior , , to prepare for clustering analysis, we used the elbow method to know the optimal number of clusters for our data. We used K-means as a clustering algorithm as unsupervised machine learning to deal with unlabeled data to clustering the data .



**Volatility Measures**

|  |  |  |
| --- | --- | --- |
| Volatility  Measure | Description | Equation |
|  | Standard deviation of speed |  |
|  | Standard deviation of longitudinal deceleration or acceleration |  |
|  | Coefficient of variation of speed |  |
|  | Coefficient of variation of longitudinal acceleration​ |  |
|  | Coefficient of variation of longitudinal deceleration |  |
|  | Mean absolute deviation of speed |  |
|  | Mean absolute deviation of longitudinal acceleration​ |  |
|  | Quantile coefficient of variation of normalized speed | , where and are the sample and percentiles. |
|  | Quantile coefficient of variation of longitudinal acceleration |  |
|  | Quantile coefficient of variation of longitudinal deceleration |  |
|  | Percentage of time the mean normalized speed exceeds the mean plus two standard deviations |  |
|  | Percentage of time the mean of longitudinal acceleration​ exceeds the mean plus two standard deviations |  |
|  | Percentage of time the mean longitudinal deceleration​ exceeds the mean plus two standard deviations |  |

**K-means Clustering Algorithm [24]**

K-means is a popular clustering algorithm for executing unsupervised learning tasks. The goal of this algorithm is to find natural groups or clusters of objects in such a way that objects in the same clusters are similar to each other and clusters in different groups are different in terms of their properties.

The outcome of the K-means algorithm is a group of clusters with corresponding centroids to minimize the following error function.

**Steps:**

**Step-1:** Select the number K to decide the number of clusters.

**Step-2:** Select random K points or centroids. (It can be different from the input dataset).

**Step-3:** Assign each data point to their closest centroid, which will form the predefined K clusters.

**Step-4:** Calculate the variance and place a new centroid of each cluster.

**Step-5:** Repeat the third steps, which means re-assigning each datapoint to the new closest centroid of each cluster.

**Step-6:** If any reassignment occurs, then go to step-4 else go to FINISH.

**Step-7**: The model is ready.-

**Minmaxscaler [25]**

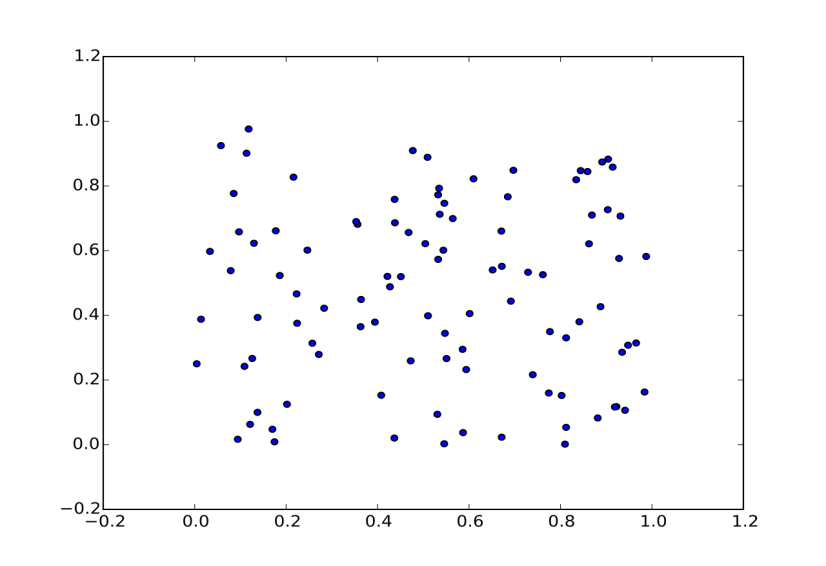
Transform features by scaling each feature to a given range.

This estimator scales and translates each feature individually such that it is in the given range on the training set, e.g. between zero and one.

**Matplot [26]**

**Matplotlib** is a plotting library for the Python programming language and its numerical mathematics extension NumPy. It provides an object-oriented API for embedding plots into applications using general-purpose GUI toolkits like Tkinter, wxPython, Qt, or GTK. There is also a procedural "pylab" interface based on a state machine (like OpenGL), designed to closely resemble that of MATLAB, though its use is discouraged. SciPy makes use of Matplotlib Pyplot is a Matplotlib module which provides a MATLAB-like interface.Matplotlib is designed to be as usable as MATLAB, with the ability to use Python, and the advantage of being free and open-source.

Matplot **e.g.** :-



**Pandas [27]**

is a software library written for the Python programming language for data manipulation and analysis. In particular, it offers data structures and operations for manipulating numerical tables and time series. It is free software released under the three-clause BSD license. The name is derived from the term "panel data", an econometrics term for data sets that include observations over multiple time periods for the same individuals. Its name is a play on the phrase "Python data analysis" itself.

**numpy [28]**

NumPy is a Python library used for working with arrays. It also has functions for working in the domain of linear algebra, fourier transform, and matrices.In Python we have lists that serve the purpose of arrays, but they are slow to process.

NumPy aims to provide an array object that is up to 50x faster than traditional Python lists.

The array object in NumPy is called ndarray, it provides a lot of supporting functions that make working with ndarray very easy.

# Analysis and Results

**Descriptive Analysis**

Using the volatility measures described above, volatility measures for each driver were found using the observed features on the highway. The id represents the driver. **Table 2** shows a sample of volatility measures for each driver.

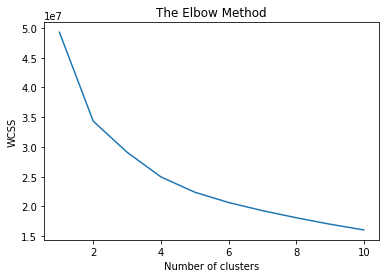
| **id** | **DV1** | **DV2** | **DV3** | **DV4** | **DV5** | **DV6** | **DV7** | **DV8** | **DV9** | **DV10** | **DV11** | **DV12** | **DV13** | **class** |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| 1 | 2.39 | 0.00 | -38.25 | 0.21 | 0.00 | 2.39 | 0.03 | 0.27 | 1.45 | 0.00 | 114.46 | 100.01 | 0.00 | Car |
| 2 | 0.09 | 0.00 | -1.41 | 0.00 | -13.57 | 0.09 | 0.02 | -0.45 | 0.00 | -33.33 | 100.14 | 0.01 | 79.12 | Car |
| 3 | 2.23 | 0.00 | -35.78 | 0.31 | 0.00 | 2.23 | 0.03 | 0.40 | 28.00 | 0.00 | 102.84 | 100.00 | 0.00 | Car |
| 4 | 0.23 | 0.01 | -3.74 | 0.45 | -16.39 | 0.23 | 0.02 | -0.06 | 60.00 | -33.33 | 100.29 | 52.18 | 27.47 | Car |
| 5 | 0.25 | 0.01 | -4.06 | 0.00 | -10.95 | 0.25 | 0.01 | -0.41 | 0.00 | -45.45 | 100.28 | 7.15 | 80.83 | Car |
| 6 | 1.83 | 0.00 | -29.36 | 0.07 | -16.98 | 1.83 | 0.02 | 0.11 | 20.00 | -39.13 | 101.98 | 78.92 | 2.72 | Truck |
| 7 | 2.16 | 0.01 | -34.61 | 0.60 | 0.00 | 2.16 | 0.03 | 1.62 | 40.00 | 0.00 | 102.21 | 100.01 | 0.00 | Car |
| 8 | 0.12 | 0.00 | -1.99 | 0.21 | -14.78 | 0.12 | 0.02 | -0.43 | 42.86 | -46.24 | 100.13 | 81.73 | 3.27 | Car |
| 9 | 0.04 | 0.01 | -0.57 | 0.18 | -14.93 | 0.04 | 0.02 | -0.32 | 13.04 | -41.67 | 100.03 | 34.98 | 51.63 | Car |
| 10 | 1.81 | 0.01 | -29.09 | 0.29 | -13.88 | 1.81 | 0.02 | 02.09 | 33.33 | -51.72 | 101.56 | 15.09 | 72.95 | Truck |
| 11 | 1.88 | 0.03 | -30.09 | 1.23 | -10.97 | 1.88 | 0.03 | 02.05 | 19.84 | -8.47 | 101.60 | 52.79 | 37.90 | Car |
| 12 | 2.21 | 0.02 | -35.49 | 0.26 | -3.40 | 2.21 | 0.01 | 2.19 | 21.05 | -5.95 | 101.56 | 43.83 | 53.78 | Car |
| 13 | 0.11 | 0.01 | -1.79 | 0.00 | -1.52 | 0.11 | 0.00 | -0.47 | 0.00 | -3.41 | 100.80 | 0.04 | 89.13 | Car |

**Table 1 V**olatility measures for each driver

**Clustering Analysis**

The elbow strategy, which uses the thirteen volatility metrics to identify the number of clusters, was used. The method involves plotting the explained variance as a function of cluster number and picking the curve's elbow as the optimal cluster number. We utilized the scikit-learn module in Python to develop the K-means clustering method [8]. The ideal number of clusters can be set as two, as shown in **Figure 2. Table 3** shows the results of conducting K-means for k = 2 using all feasible features.

**Table 3** depicts the scaled cluster centers with k = 2 utilizing all available characteristics (i.e., 13 volatility measures excluded 25% of zero data). When k = 2, aggressive and dangerous driving behaviors frequently have large volatilities [9]. When k = 2, we will assign normal and aggressive driving behaviors to the medium and large areas (**i.e**., Clusters 1 and 2), respectively.

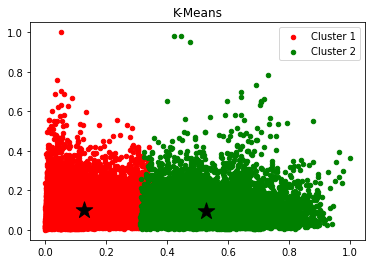
As **Figure 2** shows ,the optimal number of clusters can be chosen as two clusters

**Figure 2** Visualization of Elbow Method for K-means

**Table 3** The Scaled Cluster Centers **with**

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **DV1** | **DV2** | **DV3** | **DV6** | **DV7** | **DV8** | **DV11** | **DV12** |
| **Cluster 1 (Normal)** | 0.13 | 0.10 | 0.47 | 0.13 | 0.08 | 0.80 | 0.00 | 0.68 |
| **Cluster2**  **(Aggressive)** | 0.53 | 0.10 | 0.44 | 0.53 | 0.08 | 0.81 | 0.01 | 0.71 |

Using the remaining eight volatility measures, we next utilized the elbow technique to discover the best number of clusters. The ideal number of clusters, which can be two, is still two, as shown in **Table 3**. Therefore, we clustered driving behavior using K-means and visualized clusters using Matplot after clustering.

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# Conclusion

In light of this study that was applied in one of the highways in Germany to describe the driving behavior of the driver, we found that it can be normal or aggressive while driving on the highways through the data and there are a lot of factors that affect the driving behavior that we mentioned earlier and thus reflects the overall driving behavior On highways, drivers have their own personality and habits.

There are many things that encourage in the future to enhance and develop this technology to take advantage of it more effectively, which helps engineers

And researchers in many areas, including increasing safety on the road and giving drivers information about the behavior of drivers around them to be wary of them. In the end, the result of this study contains an important discovery in this field to build upon and prove, and sheds light on an important new understanding of highway driving behavior.

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# Contributors

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