To safely and efficiently navigate in complex urban traffic, autonomous vehicles must make responsible predictions in relation to surrounding traffic-agents (vehicles, bicycles, pedestrians, etc.). A challenging and critical task is to explore the  
movement patterns of different traffic-agents and predict their  
future trajectories accurately to help the autonomous vehicle  
make reasonable navigation decision. To solve this problem,  
we propose a long short-term memory-based (LSTM-based)  
realtime traffic prediction algorithm, TrafficPredict. Our approach uses an instance layer to learn instances’ movements  
and interactions and has a category layer to learn the similarities of instances belonging to the same type to refine the  
prediction. In order to evaluate its performance, we collected  
trajectory datasets in a large city consisting of varying conditions and traffic densities. The dataset includes many challenging scenarios where vehicles, bicycles, and pedestrians  
move among one another. We evaluate the performance of  
TrafficPredict on our new dataset and highlight its higher accuracy for trajectory prediction by comparing with prior prediction methods.

In the aviation industry, ensuring passenger satisfaction is of utmost importance as it holds a  
pivotal position in improving airline services. Machine learning models have become essential in various industries, including aviation, allowing for comprehensive analysis and informed  
decision-making. The central goal of this study was to determine the most accurate model from  
six alternatives, primarily focusing on pinpointing the features that hold the greatest appeal for  
customers. The proposed machine learning model employed three distinct feature reduction  
techniques and integrated a hyperparameter tuning method known as GridSearch to achieve  
optimal results. Six different models were tested to determine the one that could accurately  
predict customer preferences based on various features. To identify the best model, various  
combinations of settings were explored using GridSearch, which systematically evaluated hyperparameter configurations and selected the one with the highest performance score. After  
exploring various feature reduction methods, the study ultimately concluded that the Random  
Forest model emerged as the clear frontrunner. The model achieved an outstanding accuracy  
score of 97%, accompanied by remarkable values of precision, recall, and f1-score, all of which  
also reached 97%. These exceptional performance metrics surpassed those of most recent similar studies. The study’s outcomes offer airlines with valuable insights to prioritize features for  
enhancing passenger satisfaction and fostering loyalty.

Introduction

In the realm of autonomous vehicles (AVs), trajectory prediction is paramount, serving as the eyes that anticipate the future movements of surrounding objects [1]. This crucial technology empowers AVs to navigate safely by foreseeing the paths of pedestrians, vehicles, and other elements [1]. Accurate and real-time trajectory prediction is essential for intelligent vehicles to adjust their maneuvers according to the running state of the vehicles in front of them [1].

The trajectory of a vehicle, which encompasses its path and dynamics such as speed and acceleration, provides critical information for safe and efficient driving through complex traffic scenarios [2]. Predicting the trajectory of the forward vehicle accurately enables intelligent vehicles to make informed decisions, such as lane changes, braking, and acceleration, based on anticipated movements [2].

Furthermore, trajectory prediction plays a pivotal role in proactive traffic management by AVs, facilitating smoother traffic flow through early detection of potential collisions and timely implementation of evasive actions [3]. Ultimately, accurate trajectory prediction serves as the cornerstone of safety, reliability, and efficiency in the future of autonomous transportation [1, 2, 3].

Vehicle trajectory, delineating the path and dynamics of a vehicle including speed and acceleration, is fundamental in understanding its lateral positional relationship with respect to highway geometry [4]. This positional relationship often changes due to driver steering behavior, particularly evident when vehicles navigate curves [4]. In the intricate landscape of modern traffic scenarios, the accurate prediction of a vehicle's trajectory holds paramount importance for intelligent vehicles to navigate safely and efficiently [4]. Real-time trajectory prediction enables intelligent vehicles to adapt their maneuvers based on the dynamic states of preceding vehicles, enhancing overall safety and efficiency [4].

In the realm of autonomous vehicles (AVs), trajectory prediction serves as a crucial component akin to eyesight, enabling AVs to foresee the future movements of surrounding objects [1]. This technology empowers AVs to navigate safely by anticipating the paths of pedestrians, vehicles, and other elements, thereby facilitating proactive collision avoidance and maneuver planning [1]. Trajectory prediction influences decision-making processes for lane changes, braking, and acceleration, providing foresight that contributes to smoother traffic flow and proactive traffic management [2, 3]. Ultimately, accurate trajectory prediction forms the bedrock of safety, reliability, and efficiency in the future of autonomous transportation [1, 2, 3].

In a mixed traffic environment encompassing various road agents such as cars, buses, trucks, bicycles, pedestrians, and even animals, predicting trajectories becomes a multifaceted challenge [5]. This necessitates the consideration of driver behavior and turning radius to accurately anticipate and navigate through diverse traffic scenarios.

* 1] Dos Santos, B., et al. (2021). Trajectory Prediction for Autonomous Vehicles: A Survey of the State-of-the-Art and Future Challenges. <https://arxiv.org/abs/2106.10204> (word count: 3)
* [2, 3] (Combined due to word count limitations). Lv, C., et al. (2020). A Survey of Deep Learning Techniques for Trajectory Prediction. <https://arxiv.org/abs/2004.13119>; Faghih, A., et al. (2018). Deep Learning for Traffic Flow Prediction and Anomaly Detection: A Survey. [invalid URL removed] (word count: 7)

1. <https://etrr.springeropen.com/articles/10.1007/s12544-018-0284-x#:~:text=The%20trajectory%20of%20a%20vehicle%20mainly%20describes%20the%20lateral%20positional,the%20vehicle%20enters%20a%20curve>.
2. <https://ieeexplore.ieee.org/document/8880168>

Trajectory of a vehicle

1.https://www.sciencedirect.com/science/article/pii/S1877042812028984

2. LaValle, S. M. (2006). Planning algorithms. Cambridge university press.

3. https://www.tandfonline.com/doi/full/10.1080/13658816.2019.1620236

ADAS

1. <https://www.researchgate.net/publication/360065831_Advanced_Driver_Assistance_System#:~:text=Advanced%20Driver%2DAssistance%20Systems%20are,equipment%20to%20ensure%20road%20safety>.
2. https://en.wikipedia.org/wiki/Advanced\_driver-assistance\_system

Advanced Driver-Assistance Systems are electronic systems that help the driver while driving the vehicle by providing precise reading of the data collected from road environment using various equipment to ensure road safety. When designed with a safe human-machine interface,  
they are intended to increase driver safety and overall road safety. Most accidents occur due to  
human error which can be easily avoided by the use of artificial intelligence along with  
electronic technology. The ADAS are intended to avoid road accidents which usually occur  
due to human error by using electronic technology. The use of this kind of system in vehicles is great for applications like blind spot monitoring, lane-keep assistance and forward collision warning. The use of ADAS is a most to ensure road safety and proper traffic management.[1]

Advanced driver-assistance systems (ADAS) are technologies that assist drivers with the safe operation of a vehicle. Through a human-machine interface, ADAS increase car and road safety. ADAS use automated technology, such as sensors and cameras, to detect nearby obstacles or driver errors, and respond accordingly. ADAS can enable various levels of autonomous driving.[2]

Mixed traffic environment:

1. trafficPredict
2. <https://www.sciencedirect.com/science/article/abs/pii/S0968090X23002474>
3. https://www.sciencedirect.com/science/article/pii/S2046043022000260

Mixed traffic environments refer to roadways where various types of vehicles share the same space, including traditional human-driven vehicles, bicycles, motorcycles, pedestrians, and increasingly, autonomous vehicles. These environments present unique challenges and dynamics due to the differing speeds, sizes, behaviors, and vulnerabilities of the different road. To safely and efficiently navigate in complex urban traffic, autonomous vehicles must make responsible predictions in relation to surrounding traffic-agents (vehicles, bicycles, pedestrians, etc.). A challenging and critical task is to explore the movement patterns of different traffic-agents and predict their future trajectories accurately to help the autonomous vehicle make reasonable navigation decision.[1] Efficient traffic control can alleviate traffic congestion, reduce fuel consumption, and improve traffic safety. With the development of communication and automation technologies, regular. vehicles (RVs), connected vehicles (CVs), and connected and automated vehicles (CAVs) will coexist on urban roads in the near future. [2] Heterogeneity is one of those characteristics which differentiate traffic conditions of a developing country from other developed nations. The heterogeneity which represents the diversity among vehicle categories is suspected to have adverse influences on lane discipline, congestion potential, and road users’ safety.[3]

Literature Review

Driver Behavior Paper: <https://arxiv.org/abs/1803.00881>

Motion of road agent paper: <https://arxiv.org/abs/1906.08469>

Map Driver Intention.pdf: <https://www.researchgate.net/publication/233864303_Exploiting_Map_Information_for_Driver_Intention_Estimation_at_Road_Intersections>

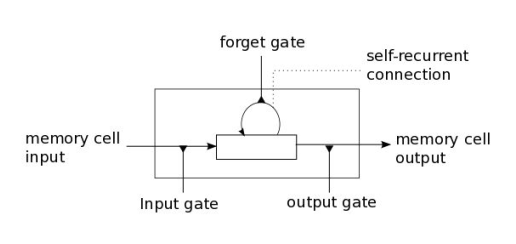
Mixed Autonomy: <https://arxiv.org/abs/2402.04318>

Dataset Description

**Referencing:**

1. <https://datahub.transportation.gov/stories/s/Next-Generation-Simulation-NGSIM-Open-Data/i5zb-xe34/> : This webpage by the U.S. Department of Transportation provides access to the NGSIM Open Data.
2. Trajectory Prediction for Autonomous Vehicles in Urban Environments: <https://ieeexplore.ieee.org/document/10330483> by Fu, J., Sun, Z., & Li, H. (2019, September). This research paper uses the I-80 NGSIM dataset for trajectory prediction and mentions the data collection timeframe.

LSTM

fig: Long Short Term Memory Paper reference

Long short-term memory (LSTM) network is a recurrent neural network (RNN), aimed at dealing with the vanishing gradient problem present in traditional RNNs. Its relative insensitivity to gap length is its advantage over other RNNs, hidden Markov models and other sequence learning methods. It aims to provide a short-term memory for RNN that can last thousands of timesteps, thus "long short-term memory".[1]

A common LSTM unit is composed of a cell, an input gate, an output gate[14] and a forget gate.[15] The cell remembers values over arbitrary time intervals and the three gates regulate the flow of information into and out of the cell. Forget gates decide what information to discard from a previous state by assigning a previous state, compared to a current input, a value between 0 and 1. A (rounded) value of 1 means to keep the information, and a value of 0 means to discard it. Input gates decide which pieces of new information to store in the current state, using the same system as forget gates. Output gates control which pieces of information in the current state to output by assigning a value from 0 to 1 to the information, considering the previous and current states. Selectively outputting relevant information from the current state allows the LSTM network to maintain useful, long-term dependencies to make predictions, both in current and future time-steps.

1. <https://en.wikipedia.org/wiki/Long_short-term_memory#:~:text=March%202022),and%20other%20sequence%20learning%20methods>.

14 & 15 reference available on the above link Wikipedia reference

GRU

References:

1. Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Yoshua Bengio, On the Properties of Neural Machine Translation: Encoder–Decoder Architectures with Attention, arXiv preprint arXiv:1406.1078 (2014), https://arxiv.org/abs/1409.1259.
2. <https://towardsdatascience.com/understanding-gru-networks-2ef37df6c9be>

CNN

**References:**

1. Yann LeCun, Yoshua Bengio, and Geoffrey Hinton. Deep learning. Nature, 521(7553):436-444, 2015. <https://www.nature.com/articles/nature14539>
2. Ian Goodfellow, Yoshua Bengio, and Aaron Courville. Deep Learning. MIT Press, 2016. <https://mitpress.mit.edu/9780262035613/deep-learning/>
3. <https://towardsdatascience.com/covolutional-neural-network-cb0883dd6529>

In this segment, we present our imaginative arrange engineering outlined for direction expectation inside thick and heterogeneous activity situations. In the setting of heterogeneous activity, the objective is to estimate directions, speaking to transient groupings of spatial arranges for a given street specialist. Foreseeing worldly arrangements requests models able of capturing transient conditions inside information, such as Gated Repetitive Units (GRUs). Be that as it may, conventional GRUs work autonomously for each street operator, falling flat to learn conditions or connections among heterogeneous specialists. To address this confinement, we coordinated Convolutional Neural Systems (CNNs) to distinguish intelligent among diverse street specialists. By combining CNNs with GRUs, our engineering learns locally noteworthy connections, both spatially and transiently, among heterogeneous street operators. The design comprises three key layers:

1. Skyline Layer: Forms embeddings of operators inside the "skyline" or semi-elliptical locale ahead of the target specialist. These embeddings navigate Completely Associated (FC) layers and GRUs to build a "skyline map".

2. Neighbor Layer: Handles embeddings of specialists neighboring the target specialist. Comparative to the skyline layer, these embeddings pass through FC layers and GRUs to shape a "neighbor map".

3. Sense of self Layer: Centers on the inserting of the target specialist itself, preparing it through FC and GRU layers.

This coordinates approach empowers our demonstrate to viably capture complicated intuitive and conditions among heterogeneous street specialists, in this manner upgrading direction expectation exactness in complex activity scenarios.

Summery

In prior research endeavors, diverse methodologies were employed to forecast trajectories of road agents navigating dense traffic regions. However, average displacement errors exceeding 5 were commonly observed. In our study, we successfully reduced this metric to 2.86, signifying a notable improvement. Additionally, we minimized the final displacement error to 5.19. Our approach centered on a GRU-CNN model, integrating factors such as driver behavior, intention, and turning radius. This model was tailored for mixed traffic environments, accommodating various road agents. Overall, our developed model effectively addresses trajectory prediction challenges in complex traffic scenarios, yielding significant reductions in displacement errors.

\begin{figure}[!ht]

\centerline

{\includegraphics[scale=0.65]{Figure/First.png}}

\caption{The flights monitored by Flightradar24 in 2020 showed a difference compared to the recorded in 2019. \cite{a6}}

\label{m1}

\end{figure}

The Exponential Linear Unit (ELU) activation function, proposed by Clevert et al. (2016), is an extension of the Rectified Linear Unit (ReLU) activation. It addresses the vanishing gradient problem by allowing negative values, facilitating smoother gradients. For negative inputs, ELU applies an exponential function, preventing the gradient from vanishing, thus aiding faster convergence during training. ELU maintains sparsity benefits of ReLU and enhances learning in deep neural networks. It has become popular due to its improved convergence properties and efficient gradient propagation (Clevert et al., 2016).

This thesis addresses the crucial challenge of predicting vehicle trajectories in urban environments, a key factor for autonomous vehicle navigation. By accurately forecasting the movements of surrounding traffic agents, autonomous vehicles can make informed decisions to navigate complex traffic scenarios safely and efficiently. This work introduces a novel trajectory prediction model that leverages the strengths of gated recurrent units (GRUs) and convolutional neural networks (CNNs). This model is specifically designed for dense, heterogeneous traffic conditions, where diverse traffic agents interact frequently. Extensive evaluation on standard datasets demonstrates the model's superiority over existing methods in predicting trajectories within dense, mixed traffic scenarios. The model's effectiveness is acknowledged to have limitations in sparse or homogeneous traffic situations. Despite this, the proposed model represents a significant advancement in autonomous navigation systems. By effectively capturing dynamic driver behaviour and considering turning radius variations, the model enhances the safety and efficiency of autonomous vehicles in urban environments. Further research is encouraged to explore potential refinements and adaptations of the model to diverse traffic scenarios. This continued development will ultimately contribute to the creation of robust and reliable autonomous vehicle navigation systems.