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Personalized Driver Behavior Prediction for Safe Driving using Smartphone

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Research Snippets

Introduction

The current transportation business scenarios lack an adequate system that ensures safe driving recommendations with maximum taxi drivers' hours of service. According to statistics, there were a total of 4,80,652 number of road accidents claiming 1,51,113 lives in the year 2019 in India. In these road accidents, taxi drivers also have a significant ratio, and long working hours is one of the major causes of accidents. Companies like Ola, Uber, Grab, Meru, Mega, etc. offer high incentives to complete more trips that encourage taxi drivers to accept frequent trips without taking rest, but this also leads to abnormal driving behavior such as rash driving, swerving, side-slipping, sudden brakes, weaving, and accidents in the worst cases. By identifying driving behavior correctly, these accidents can be reduced by 10%-20%. Therefore, as the road accidents rise per year, our motivation is to provide an economical, adaptable, efficient, and easily deployable recommendation system for driver and passenger safety that will provide an appropriate balance between income and health [1]. The system suggests the driver to accept or reject the next trip along with the option to follow alerts during the trip based on predicted driving behavior.

Research has been carried out for many years to provide efficient recommendation systems that reduce trip time, waiting time, overall trip cost for customers, and minimize idle time, increase profit for taxi drivers. Nevertheless, these recommendation systems pay less attention towards driver's health and road safety. We address the problem of safety and health among drivers by predicting driving behavior. However, the driving behavior has been extensively studied before, and the study revolved around driver attention, intention, behavior, drowsiness, etc. These studies have a common objective of understating driving status using physiological and psychological data and providing a safe driving system. In contrast, we analyse driver behavior for the task of prediction using sensor recorded data. Additionally, behavior prediction done using smartphone instead of On-Board Unit (OBU), i.e., communication device mounted on vehicles that are difficult to deploy at large scale due to the cost associated with them.

Problem Statement and Challenges

The problem we want to solve is to develop an adaptable, economical, easily deployable system that provides safety to drivers, passengers, and entities outside the taxis by predicting driver behavior to recommend the next trip. Challenges to solve the problem of driver behavior prediction are: (1) Identifying factors that contribute to the driver's behavior. (2) A generic model that captures individual personality traits. We resolve the issues by identifying direct and indirect factors that contribute to the driver's behavior based on existing studies. For generalization, we can use a multi-task learning model to identify the personality traits of the individual driver.

Methodology

We solve the problem of developing a recommendation system that automatically learns individual driving behavior characteristics by dividing the task into four stages as in a machine learning problem: (1) Data Collection, (2) Feature Extraction, (3) Modeling Driver Behavior, and (4) Trip Recommendation.

1. We can use publicly available dataset like UAH-DriveSet dataset that is collected by a driving monitoring app, one of such app named DriveSafe that has data of a total of six drivers, or we can collect our own dataset. The dataset records data collected by smartphone inertial sensors as well as Global Positioning System (GPS) data with the video clip for all the trips. The driving data is for 500 minutes and labeled with driving behavior such as normal, drowsy, and aggressive.

2. Next step is to identify significant factors that cause road accidents. These factors depend on the driver, vehicle, road conditions, or weather conditions based on the statistics. We categorize the factors in the form of base features as trip data, driver demographics, vehicle data, road environment, environmental data, and traffic data. There is another category called derived features extracted from base features using statistical properties such as mean, variance, standard deviation, maximum, and minimum. The inspiration behind these features is to relate direct and indirect factors to the behavior of the driver. Since all the input features are not in the same range, that will affect the model performance. Therefore, normalization of extracted features is necessary.

3. The main challenge in the stated problem is modeling driving behavior under dynamic driving conditions. Here, dynamic driving conditions mean the driving environment changes with time, and all the factors are not static. Every driver has a different behavior, such as aggressive driving, which may be one driver's style. In contrast, another driver is affected by direct or indirect factors that result in aggressive driving. So, the model should capture the difference. We can use Multi-task learning (MTL) [2] based models that personalize the driver behavior. As the dataset is labeled with behavior, supervised deep learning is applicable on extracted features. We introduce multi-task learning with attention architecture for predicting driver behavior. Multi-task learning can be incorporated into any neural network; we use a simple multi-layer perceptron. This configuration allows us to predict driver behavior for the next trip. MTL model is used in many recommendation systems where it fulfills the requirement of capturing personalized information, so it can be used to personalize the driving behavior prediction task. MTL can learn different tasks in a single model. In our case, a single driver behavior prediction is one task. We used a shared bottom approach of multi-task learning Neural Network (MTL-NN) as shown in Figure 1.

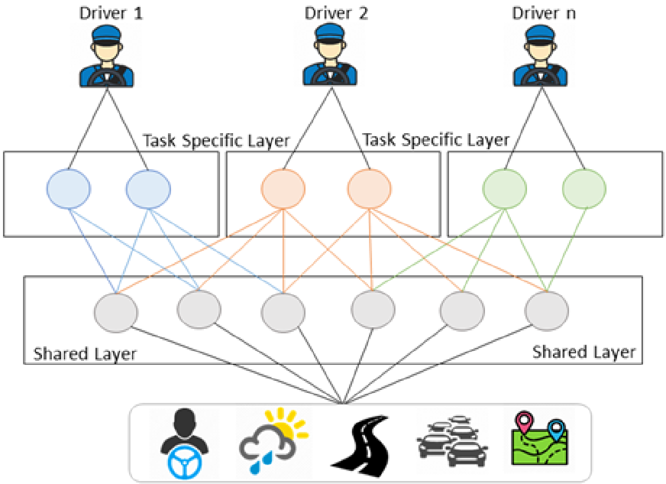

Figure 1: MTL-NN overview for driver behavior prediction

In the shared bottom approach, the first layer of MTL-NN is a shared layer that captures common features for all the drivers that affect driver behavior. The next layer is a task-specific layer called a tower that captures individual personality traits for each driver. Performance measures are used to evaluate the model quantitatively, we can use performance measures, namely, Accuracy and F-measure as metric for evaluation as they are popular metrics for classification.

4. Trip recommendation is explained with the help of Figure 2. The driver provides the trip details, and features are extracted from the data. Behavior prediction model used to predict driving behavior and according to the prediction, Mobile App suggest options to drivers such as accept or reject. In the recommendation, two scenarios arise: first one is if the driver's behavior is drowsy or aggressive, the system recommends to reject the trip. Second, if the behavior of the driver is normal, then the system recommends to accept the trip.

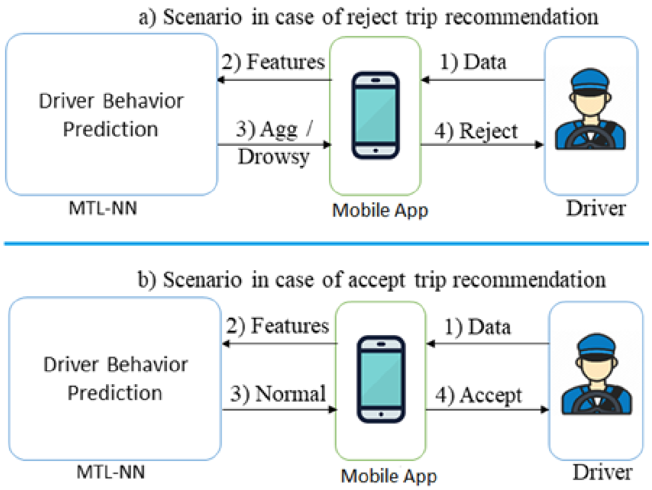

Figure 2: Trip recommendation scenarios

Applications

This recommendation system has a vast area of applications in fleet management, insurance services, taxi services, transport service, and advanced driver-assistance systems. How our system is beneficial in these applications is further explained in detail:

1. Fleet management includes functions such as vehicle tracking and maintenance, driver management, speed, health, and safety management. Existing fleet management software lacks driver behavior analysis for driver and vehicle safety. Our system can provide services to fleet managers as they can monitor driver behavior and provide rewards or incentives if they have good driving behavior. This will not only reduce the risk of accidents as well as ensure the safety of driver and vehicle.
2. Insurance companies like Bajaj Allianz, Bharti AXA, HDFC ERGO, etc., set premiums to the driver based on age, gender, vehicle type, place of residence, etc. However, these features provide less predictability of risk taken by drivers. By using our system, insurance services providers can monitor their policyholders and reduce information asymmetry between them. If a driver has rash driving behavior and meets with an accident, the insurance companies can form policies to provide the minimum required claim or provide discounts to drivers based on driving behavior.
3. The demand for taxi services increased a lot in recent years, creating a need for an automated system to monitor taxi driver behavior. Our system will help taxi service providers like Ola, Uber, Meru, etc., by predicting behavior in the next trip to avoid any accident. The taxi service provider may provide more incentives and trips to the driver that have good driving behavior. It will increase the quality of service and ensure the safety of drivers.
4. ADAS assists the driver for car and road safety using multi-modal data by monitoring, braking, warning, etc. Conventional Advanced driver-assistance systems (ADAS) technology can detect objects, alert the driver of hazardous road conditions, and in some cases, slow or stop the vehicle. With the help of our system additional functionality can be added to ADAS that will recommend the trip to the driver according to its behavior and provide ongoing trip alerts.

Advantages and Future Scope

The solution is easily deployable and economical in the form of mobile application; as maximum drivers have smartphones to access services. Therefore, no additional hardware is required for deployment, additionally it also reduces overhead of maintenance as the vehicle will be safer from wear and tear costs caused by aggressive driving. We are planning to extend our work for privately owned vehicles that recommend drivers with alerts to reduce their stress level.

References

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