Data-driven Robust Scoring Approach for Driver Profiling Applications

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***Abstract*—Driving behavior profiling has important relevance in many driving applications. For instance, car insurance companies have been recently applying a new insurance paradigm in which a driver's insurance premium is adapted based on real-time driving behavior. Driver profiling process is composed of two sub processes. The first is the detection of certain driving behaviors by acquiring data from onboard devices such as smartphones and OBDII units, whereas the second is the scoring process in which the detected behaviors are used to measure the actual driving risk. The scoring process has been viewed as an intricate problem due to the lack of reliable and large-scale datasets that can provide statistically trustworthy insights. This paper presents a data-driven approach for calculating a driver's risk score by utilizing the SHRP2 naturalistic driving dataset, which is the largest dataset of its kind to date. Two machine learning algorithms, which are support vector regression (SVR) and decision tree regression (DTR) are trained to reflect a driver's score. Driver's score is quantified in terms of the additive inverse of the predicted risk probability. After data filtering and preprocessing, models are trained using thirteen predictors, which represent twelve unique driving behaviors and the total driving time per driver. Validation results show that risk probability can be accurately predicted using the proposed models.**

***Index Terms*—Internet of vehicles (IoV), driving behavior profiling, data driven applications, intelligent transportation systems (ITS), machine learning, prediction models.**

I. Introduction

Despite all the recent developments in road safety systems, road crashes are still in the top ten leading causes of death worldwide [1]. For instance, road crashes were the fifth main reason of deaths in Canada in 2015, which constitutes 4.5 % of the overall number of fatalities [2]. As a result, researchers in academia and industry have been proposing new innovative ideas to tackle this problem. A particularly emerging driving safety application is driver risk profiling which has gained a special significance in the fleet management and car insurance telematics domains [3]. In fleet management domain, fleet administrators are interested in tracking the behavior of their drivers to ensure the safety of their fleets. Likewise, car insurers have been recently adopting a new insurance paradigm called pay-how-you-drive (PHYD) in which insurance premium is adapted according to the real-time behavior of drivers [4]. In both domains, data that reflects a subject drivers's (sd) behavior is collected using smartphone sensors and/or on-board diagnostics (OBD) units, and is then analyzed to detect certain behaviors. Different figures of merit (FOMs) are typically calculated for each trip using the collected data. Conventionally, there are four driving behavioral FOMs insurance companies utilize as risk quantification measures (i.e., risk predictors) to calculate risk scores. These FOMs are: braking, speeding, acceleration and cornering behaviors [4].

Modeling the actual risk score based on the calculated FOMs is viewed by many as an intricate problem. The reason is that the process of designing efficient scoring models necessitates the existence of enough and reliable data, which is not always available [4]. Consequently, different insurance companies have been adopting several scoring models that assign different weights for each FOM [4]. Although several insurers are viewing the number of harsh braking events as the best risk predictor, there is no common agreement about the statistical significance of such measure.

SHRP2 Naturalistic Driving Study (NDS) dataset offers an enormous amount of driving context data for almost 9,000 recorded crash and near crash events and more than 20,000 balanced base-line events (i.e., normal driving events proportional to the total driving per driver) [5]. The data collected not only gives the opportunity to study the prevalence of behavioral factors during risky events, but also their prevalence through normal driving episodes, which enables the conduction of statistically sound studies. The contribution of this paper is threefold:

1) It provides a robust data-driven framework for predicting a driver's risk probability by utilizing the behavioral context information during base-line, crash and near crash events. To achieve this, twelve behavioral risk predictors are identified and the feature matrix is formulated. Driving score is then expressed in terms of the additive inverse of the predicted risk probability.
2) Two machine learning algorithms, which are support vector regression (SVR) and decision tree regression (DTR) algorithms, are employed to reflect a driver's predicted risk probability. Both algorithms are compared in terms of their average performance and their performance consistency through various testing samples. The algorithms are trained and tested using an unprecedented amount of data for more than 2,000 drivers.

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3) An important finding is that driving risk can be accurately predicted with only few events captured with an appropriate sampling time (i.e., balanced base-line events). Therefore, there is no need for a continuous driving data acquisition to determine the associated risk of a certain driver. This has its relevance in minimizing the consumed power of offloading driving data to the cloud server and minimizing the computational cost for predicting driving risk.

The remainder of this paper is structured as follows. In section II, a background review and the related work are provided. Section III presents the formulation of the driver scoring problem. In section IV, the adopted data filtering and preprocessing process is described. In section V, the implementation details of the underlying algorithms that have been utilized to tackle the risk prediction problem are presented. Results and discussion are presented in section VI and Conclusions are drawn in section VI.

II. Background and Related Work

A. Driving Behavior Profiling

Driver behavior profiling is of interest to industry and academia. Several industrial products as well as research papers have been implemented and proposed. For instance, car insurance companies have developed different smartphone applications that are compatible with IOS and Android operating systems and are capable of detecting and evaluating the behavior of drivers by utilizing smartphones' sensors such as: accelerometer, magnetometer and GPS sensors. Examples include Aviva RateMyDrive and StateFarm DriverFeedback applications [6], [7]. The aggregated scores over many trips are used to adjust the drivers' insurance premiums.

On the other hand, research in this field has been in two main streams:

1) Driver behavior detection and classification. This includes the detection of certain events such as: aggressive acceleration, aggressive lane change, etc. [8], [9].
2) The development of a scoring function that accurately reflects risk rate given the detected behaviors [3], [10].

While the earlier contains many contributions, the latter has very few. Indeed, the choice of scoring functions has been very subjective due to the absence of a frame of reference due to the lack of large-scale and reliable datasets.

In [8], authors proposed an HMM-based model to detect sharp and normal driving maneuvers in both longitudinal and lateral directions. Events were detected using smartphones and authors claimed to have a classification accuracy of $\sim$ 95%. Authors in [11] proposed an application called MobiDriveScore that acquires data from a smartphone and a vehicle's network (i.e., CAN-bus) to detect risky events. A smartphone application called CarSafe was proposed in [12] to detect dangerous behaviors. Authors utilized smartphones' dual cameras to detect a number of dangerous events. They used the front camera to detect drowsiness and distraction whereas the rear camera was utilized to detect tailgating and unintentional lane changing. A fuzzy logic based smartphone application was proposed in [3]. In this work, a complete driving behavior detection and scoring system was proposed and discussed. Four unique driving events were detected with high accuracy by fusing smartphone's accelerometer, gravity, magnetic, and GPS data. Moreover, authors used two different smartphones with different sampling rates and resolution and compared their detection performances which were found to be consistent. More recently, authors in [13] proposed an HMM-based modeling approach that is capable of classifying the behavior of drivers by taking into account the behavior of surrounding vehicles. Models were trained and tested using the 100-CAR NDS dataset.

Despite all the aforementioned efforts in event detection and driver behavior classification field, contributions in formulating reliable scoring functions are still very primitive [3], [4], which motivated the formulation of reliable data-driven scoring models presented in this work. In this work, the risk probability, quantified in terms of crash and near crash events' rate, is predicted by considering the rate of occurrence of different driving behaviors and the total driving time per driver.

B. SHRP2 NDS Dataset

Human errors contribute in approximately 90% of crashes [14]. In order to examine the influence of different driving behaviors on the crash rate, different approaches have been proposed including the naturalistic driving (ND) data collection approach. ND data collection methodology provides three important advantages over other methods [15]:

1) Detailed information about the behavior of a driver prior to a crash/near crash events.
2) Exposure information, which provide vital information about the frequency of occurrence of different driving behaviors during normal driving episodes.
3) The amount of collected data which paves the way for conducting statistically sound studies.

The Virginia Tech Transportation institute (VTTI) has been pioneering this approach since the beginning of this century with two large-scale data collection projects; the 100-CAR NDS and more recently the SHRP2 NDS [5], [15]. In SHRP2 NDS, 3542 drivers were recruited in six different sites in the United States, and their vehicles were equipped with unobtrusive data acquisition systems (DASs) containing mainly forward radar sensors, video cameras, OBD units to acquire the vehicle's CAN bus information, and global positioning system (GPS). Participants were then asked to use their vehicles as in their normal day-to-day driving routine. Some participants remained for the entire course of the project and others were replaced. Data was continuously recorded which resulted in more than 35 million miles of driving data. This is, by far, the largest amount of naturalistic driving data ever recorded. Data reductionists were then able to extract almost 9,000 risky events which are comprised of crashes and near-crashes. Moreover, more than 20,000 normal driving events where randomly captured for drivers to offer exposure information. These episodes are called balanced baseline events as their

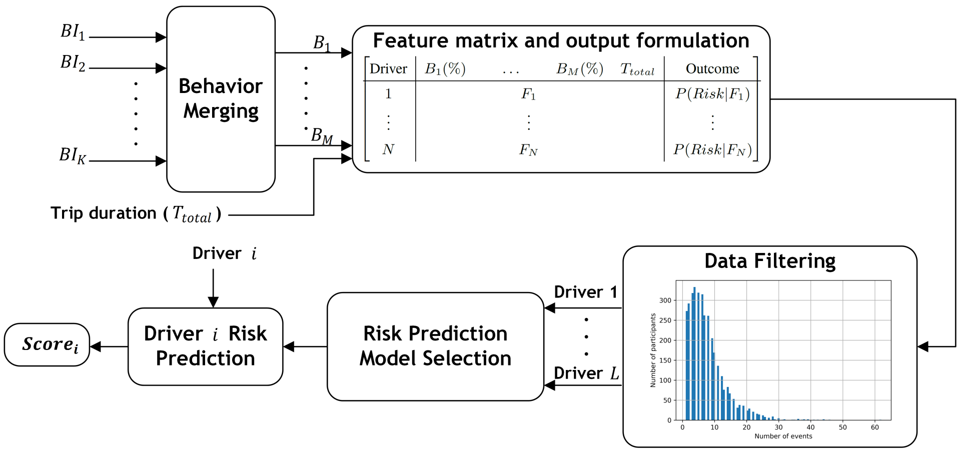

Fig. 1: Block diagram of driver's risk scoring system

number is proportional to the total driving time of a driver. A total of 59 driving context behavioral attributes have been identified during recorded events by VTTI data analysts. The operational definitions for each type of these events can be found in [5] and are briefly as follows:

1) Crash: Any contact that the sd makes with an object (vehicle, pedestrian, cyclist, animal, etc.), either moving or fixed. Also includes inadvertent departures of the roadway.
2) Near crash: Any driving conflict that requires an evasive action to avoid a crash.
3) Balanced baseline events: epochs of data selected to provide exposure information. They are 21 seconds long and their number is proportional to the total driving time for each driver.

The detailed selection criteria of the number of baseline events per driver can be found in [16]. The dominant driving behavior prior to crash/near crash events or during baseline events was extracted and recorded by VTTI data analysts using the collected data.

III. Problem Formulation

Let F_{ID} represents the feature vector that holds the behavioral FOMs of driver ID after driving for T_{total} seconds. It can be expressed mathematically as:

$$F_{ID} = \begin{bmatrix} B_1(\%) & \dots & B_M(\%) & T_{total} \end{bmatrix} \tag{1}$$

where the vector entries "$B_i(\%)$" represent the frequency of occurrence of each behavior with respect to other behaviors and T_{total} is the total exposure (driving) time of a trip. In this paper, 12 mutually exclusive driving behaviors have been identified as risk predictors. They are depicted in table I with their brief description. The detailed selection criteria is explained in section IV.

The risk score for driver ID at trip j is calculated in terms of the conditional risk probability $P(Risk|F_{ID})$ as:

$$Score_{ID}(j) = 1 - P(Risk|F_{ID})_j \tag{2}$$

where $P(Risk|F_{ID})$ is the predicted risk probability which is governed by the summation of the crash (C) and near crash (NC) conditional probabilites as shown in equation 3:

$$P(Risk|F_{ID}) = P(C|F_{ID}) + P(NC|F_{ID}) \tag{3}$$

The choice of a prediction model that can accurately predict $P(Risk|F_{ID})$ is very crucial for obtaining a reliable score. In this work, SVR and DTR, which are two of the most powerful machine learning algorithms, are utilized for this purpose. Figure 1 depicts the complete flowchart of the proposed risk scoring system. Each of the components is discussed in the following sections.

IV. Data Filtering and Preprocessing

A. Feature Selection

As previously stated, 12 driving behaviors as well as the total driving time, reflected in terms of the total number of base-line events for each driver, are used as risk predictors to train and validate proposed models. Based on the adopted selection criteria, the selected behaviors are comprehensive and mutually exclusive in nature. They are chosen according to the following procedure:

1) In the SHRP2 dataset, driving behaviors are classified into 59 unique behaviors, which span all possible driving behaviors. In the dataset, the three most apparent behaviors in a captured event are sorted according to their dominance inside the event time frame. For simplicity, only the most dominant behavior is chosen, which makes behaviors mutually exclusive for a given event. This eliminates having to apply additional orthogonalization techniques, such as Principal Component Analysis (PCA) algorithm, for correlated features.
2) Behaviors that can be possibly put under the same category are combined to increase features' importance. For instance, all sign and signal violation behaviors are put under the common behavior: "Signal or sign violation". By following the same procedure for other

TABLE I: Summary of driving behaviors

Behavior	Description
Excessive speeding	Exceeding safe speed/ speed limit
Inexperience or unfamiliarity	Apparent general inexperience driving, unfamiliarity with a vehicle or a roadway
Avoiding an object	Avoiding a vehicle, pedestrian, or an object
Sudden braking	Sudden or improper stopping on a roadway
Right-of-way error	Right-of-way error due to decision or recognition failures, or other unknown cause
Driving slow	Driving slowly in relation to other traffic or below speed limit
Improper backing	Improper backing due to inattentiveness or other causes
Illegal or unsafe lane change or turn	Any improper or illegal lane change or turn
Aggressive driving	Such as aggressive acceleration or aggressive lane changing
Signal or sign violation	Violation action at traffic signs or signals
Safe	No sign of risky behavior
Fatigue & neglectance	Includes drowsiness, failure or improper signaling, and driving without lights

behaviors, a total of 12 distinct behavioral categories are formulated.

The initial training and validating dataset is then formulated as shown in equation 4.

$$\left[\begin{array}{c|cccc|c} \text{Driver} & B_1(\%) & \dots & B_M(\%) & T_{total} & \text{Outcome} \\ \hline 1 & & F_1 & & & P(Risk|F_1) \\ \vdots & & \vdots & & & \vdots \\ N & & F_N & & & P(Risk|F_N) \end{array}\right] \tag{4}$$

B. Data Filtering

The initial formulated dataset was filtered to remove drivers who has an unrepresentative number of captured events. A sensitive analysis was applied to find the minimum optimal number of events a driver should have to be included ($E_{optimal}$). The tradeoff was to find the best model performance in terms of model's mean square error (MSE) without losing too much data. Figure 2 depicts the histogram distribution for the number of captured events for all drivers contributed in the SHRP2 project. A marginal enhancement in the proposed models' average performance was obtained with $E_{optimal} > 6$. So, an $E_{optimal} = 6$ was adopted as a filtering criteria.

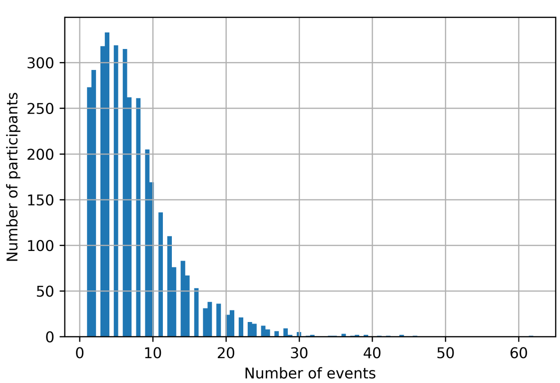

Fig. 2: Histogram distribution for the number of captured events for drivers in the SHRP2 dataset.

C. Feature Scaling

SVR algorithm does not work efficiently without feature normalization. That is because if one of the features has a broader range of values than others, the aforementioned algorithm will be biased to this specific feature since the minimum distance will be governed by it. As a result, it is always a good practice to have the same range of values for all features. In this work, feature normalization was applied to the SVC model. The following normalization equation was adopted:

$$\hat{X} = \frac{X - \mu_x}{\sigma_x} \tag{5}$$

where X is the raw feature vector. $\hat{X}$ is the normalized feature vector, μ_x is the mean of X and σ_x is the standard of deviation of X.

V. Implementation

This section presents the adopted implementation details for SVR and DTR algorithms that are used to predict drivers' risk probability $P(Risk|F_{ID})$. The algorithms are implemented in Spyder (Python 3.6) integrated development environment (IDE) using the scikit-learn library for machine learning and data mining. All the tests were performed on a 3.40 GHz, intel core i7-2600 CPU. The adopted training and testing splitting approaches for these models as well as the choice of their hyper parameters are presented next.

A. Training and testing splitting Methodologies

Two Training and testing splitting approaches have been adopted to train and validate the models.

1) *General splitting approach*: This is the common approach of choosing a randomly selected portion of the dataset for training and use the rest for testing. The splitting ratio usually depends on the amount of collected data and the application. In this work, 75% of the dataset was utilized for training. As a result, 1505 training samples and 502 validation samples were used.
2) *K-fold cross validation*: In this approach, the entire dataset is randomly divided into K equally sized partitions. In each training/ testing cycle, a single partition

is kept for testing and all the remaining partitions are used for training. Training and validation is performed K times with each of the single partitions used exactly once for testing. The mean and standard of deviation of the results can then be obtained to have more a statistical reflection on the model's performance. This approach is superior over the other approach since all data samples are utilized for both training and testing. In this work, a *10-fold cross-validation* is adopted for all models.

B. Hyper parameters optimization

In order to achieve the best performance for the two prediction models, different hyper parameters for each model need to be optimized. In this work, grid search technique is applied to find the best hyper parameters for each model. In this technique, different values for each parameter are specified and the performance is computed exhaustively for each combination. The algorithm returns the hyper parameters combination that led to the best performance. The adopted performance metric for grid search is the mean square error and a *10-fold cross-validation* is applied.

1) SVR: The optimization is performed over four hyper parameters which are: the regularization parameter C, the kernel function k, the tolerated margin of error ϵ, and the sensitivity parameter γ. The parameter C is necessary to avoid the overfitting problem. It determines which training samples are considered as outliers. The k parameter specifies the kernel type. For instance, a linear kernel means that SVR will use linear separation hyperplanes. The ϵ parameter defines a tolerance margin in which no penalty is applied to errors. And finally the γ parameter is a sensitivity parameter to measure the similarity between the feature vectors. For instance, if γ is large, feature vectors will be considered similar only if the Euclidean distance between them is small. A more detailed explanation of these hyper parameters could be found in [17]. Table II shows the investigated hyper parameters and the best combination is shaded.

TABLE II: SVR adopted Hyper-parameters

Parameter	**Values**				
Kernel	Linear	Polynomial	Gaussian radial basis	-	-
C	1	5	10	50	100
ϵ	0.01	0.05	0.1	0.2	0.3
γ	0.01	0.05	0.7	0.1	0.2
Poly degree	2	3	4	5	6

2) DTR: Only two hyper parameters are optimized. The first is the decision tree maximum depth (MD), while the second is the criterion of choosing the best split point in each feature's histogram (CR). Table III depicts the hyper parameters used and the best combination is shaded.

VI. Results and Discussion

The best hyper-parameters' combination for each of the two algorithms is adopted to measure their performance results. Table IV shows the MSE, MAE and R^2 performance results for DTR and SVR algorithms using the general splitting approach. Both algorithms seem to have good performance results with some advantage of SVR over DTR. A particularly important metric is the R^2 which reflects the percentage of variance in the outcome that the model can explain. As for this metric, the results show that the SVR algorithm has a difference gain of 12% over DTR.

TABLE III: DTR adopted Hyper-parameters

Parameter	**Values**			
Split Criterion	MSE	MAE	-	-
Tree maximum depth	6	7	8	9

TABLE IV: Prediction performance results using general splitting approach

	Performance measures		
Algorithm	MSE	MAE	R^2
DTR	0.017	0.1	0.38
SVR	0.014	0.086	0.5

To examine the consistency of these results over different training and testing samples, a *10-fold cross-validation* is applied and the results are depicted in figure 3. Although the SVR algorithm is consistently achieving better performance results in the average sense, it is less consistent over the individual training/ testing samples. This can be shown in the extended whisker plot ranges especially for R^2 metric which makes DTR more preferable over SVR. The summary of these results are shown in table V.

TABLE V: Prediction performance results using 10-fold cross-validation

	Performance measures		
Algorithm	Average MSE	Average MAE	Average R^2
DTR	0.016	0.096	0.47
SVR	0.0159	0.090	0.48

VII. Conclusion

In this paper, a data-driven robust framework for calculating risk score for driver profiling applications was presented. Predicted risk probability was adopted to signify a driver's risk score. By utilizing the behavioral driving context information and the total exposure time for more than 2,000 drivers from SHRP2 dataset, two risk predication models were devised and compared. Two model training approaches, which are the general splitting and *10-fold cross validation* approaches, were adopted and the results show that these models can accurately predict the risk probability. One important finding is that driving risk for a certain driver can be accurately predicted with only few events captured with an appropriate sampling time. The SVR model seems to outperform the DTR in all performance measures with a consistency advantage for DTR over SVR for different training/testing samples.

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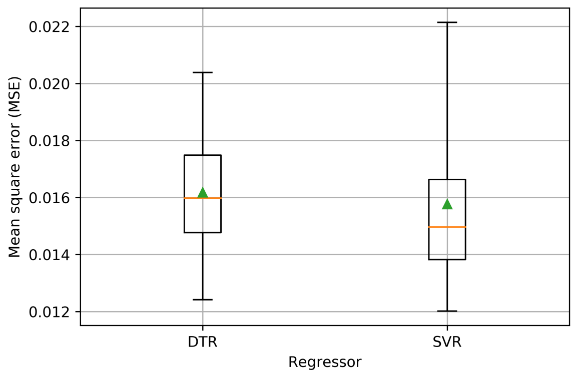
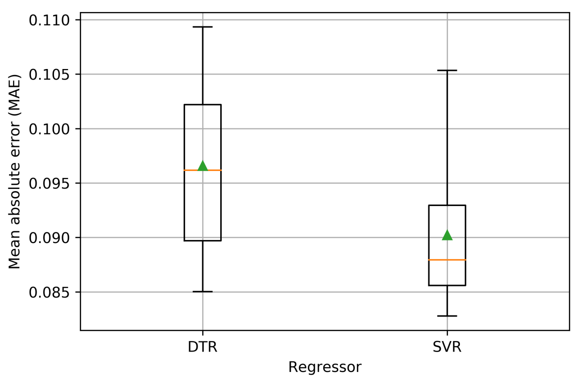
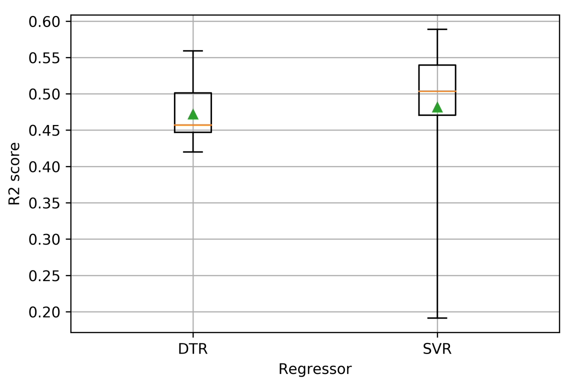


(a) MSE



(b) MAE



(c) R^2 score

Fig. 3: Whisker plot for MSE, MAE and R^2 performances using 10-fold cross-validation.

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