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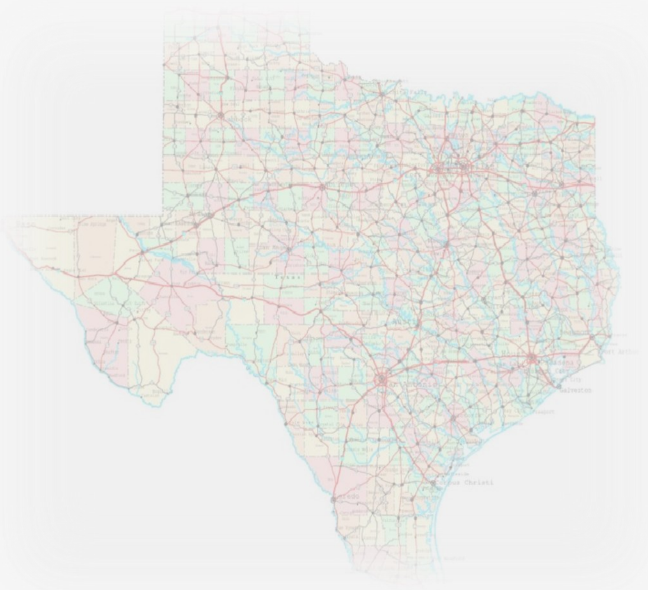
RESEARCH

Development of a Statistical Method for Predicting Human Driver Decisions



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Development of a Statistical Method for Predicting Human Driver Decisions

Report: ATLAS-2015-06

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September, 2015

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ACKNOWLEDGEMENT

This research project was supported by the Center for Advancing Transportation Leadership and Safety (ATLAS Center). The ATLAS Center is supported by a grant from the U.S. Department of Transportation, Office of the Assistant Secretary for Research and Transportation, University Transportation Centers Program (DTRT13-G-UTC54). The ATLAS Center is a collaboration between the University of Michigan Transportation Research Institute (UMTRI) and the Texas A&M Transportation Institute (TTI). We would like to thank Dr. Shan Bao and Dr. John Sullivan for their help in obtaining the data extract used in this study. Dr. Bao also provided invaluable help in understanding the codes and signals present in the dataset. Support for this research was provided by a grant from the U.S. Department of Transportation, University Transportation Centers Program to the ATLAS Center.

Technical Report Documentation Page

1. Report No.
ATLAS-2015-06

2. Government Accession No.

3. Recipient's Catalog No.

4. Development of a Statistical Method for Predicting Human Driver Decisions

5. Sept 30, 2015

6. Performing Organization Code

7. Yaoyan Vincent Tan, Michael Elliott, Carol Flannagan

8. Performing Organization Report No.

9. Performing Organization Name and Address
University of Michigan Transportation Research Institute (UMTRI)
2901 Baxter Rd.
Ann Arbor, MI 48103

10. Work Unit no. (TRAIS)

11. Contract or Grant No.
DTRT13-G-UTC54

12. Sponsoring Agency Name and Address
Advancing Transportation Leadership and Safety (ATLAS) Center
2901 Baxter Rd., Room 124,
Ann Arbor, MI 48109-2150 U.S.A

13. Type of Report and Period Covered

14. Sponsoring Agency Code

15. Supplementary Notes
Supported by a grant from the U.S. Department of Transportation, OST-R, University Transportation Centers Program

16. Abstract
As autonomous vehicles enter the fleet, there will be a long period when these vehicles will have to interact with human drivers. One of the challenges for autonomous vehicles is that human drivers do not communicate their decisions well. However, the kinematic behavior of a human-driven vehicle may be a good predictor of driver intent within a short time frame. We analyzed the kinematic time-series data (e.g., speed) for a set of drivers making left turns at intersections to predict whether the driver would stop before executing the turn or not. We used principal components analysis (PCA) to generate independent dimensions that explain the variation in vehicle speed before a turn. These dimensions remained relatively consistent throughout the maneuver, allowing us to compute independent scores on these dimensions for different time windows throughout the approach to the intersection. We then linked these PCA scores to whether a driver would stop before executing a left turn using the Bayesian additive regression trees (BART). Our model achieved an area under the receiver operating characteristic curve (AUC) of more than 0.90 by -25m away from the center of an intersection.

17. Key Words
Statistics, Decision-Making, Prediction Algorithm, Automated Vehicles, Bayesian Additive Regression Trees, Naturalistic Driving Data, Principal Components Analysis

18. Distribution Statement
Unlimited

19. Security Classification (of this report)
Unclassified

20. Security Classification (of this page)
Unclassified

21. No. of Pages
14

22. Price

1 Introduction

An autonomous vehicle can be loosely defined as a vehicle that needs no human supervision or human control. The National Highway Traffic Safety Administration (NHTSA) provides a more detailed definition with five levels of classification (NHTSA, 2013):

Level 0: The driver completely controls the vehicle at all times.

Level 1: Individual vehicle controls are automated, such as electronic stability control or automatic braking.

Level 2: At least two controls can be automated in unison, such as adaptive cruise control in combination with lane keeping.

Level 3: The driver can fully cede control of all safety-critical functions in certain conditions. The car senses when conditions require the driver to retake control and provides a "sufficiently comfortable transition time" for the driver to do so.

Level 4: The vehicle performs all safety-critical functions for the entire trip, with the driver not expected to control the vehicle at any time. As this vehicle would control all functions from start to stop, including all parking functions, it could include unoccupied cars.

Society of Automotive Engineers (SAE) International provides an alternative classification system (SAE International, 2014), but in this study we utilize the NHTSA classification and viewed an autonomous vehicle as a Level 4 classification.

One of the challenges for deployment of Level 4 automation is that automated vehicles will have to interact with human drivers in other cars. Unfortunately, human drivers do not always communicate their decisions clearly, leading to near crashes and crashes. Because of this, these autonomous vehicles will have to learn how to predict human-driver decisions using information conveyed by the human driver's vehicle.

In this study, we hypothesized that the kinematic behavior of a human-driven vehicle would provide enough information to make a good prediction of driver intent within a short time frame. In particular, we studied the kinematic behavior of a human-driven vehicle, based on the vehicle's speed. We focused on the prediction of whether a human driver would stop at an intersection before executing a left turn. We believe that once the prediction model of such a simple driving behavior is fine-tuned to produce satisfactory prediction results, we can then extend this model to other forms of driving behavior. Our ultimate goal is to develop a prediction model of human driving behavior using the vehicle speed from the human-driven vehicle.

To build the prediction model, we used naturalistic driving data from about 100 licensed drivers in Michigan. We converted the time-series data to a distance series and defined a new distance-varying outcome. Because it seems likely that recent speeds contain more information about the human driver's intention to stop compared with past speeds, we employed a moving window on the distance-varying speeds. We next used Principal Components Analysis (PCA) to reduce the number of variables used in our prediction algorithm. To link our distance-varying outcomes to our Principal Component (PC) variables, we used the Bayesian Additive Regression Trees (BART). We evaluated our BART model's prediction performance at every meter away from the center of an intersection by using the Area Under the receiver operating characteristic Curve (AUC). Finally, to visually search for an optimal predicted probability cutoff level that would balance both unnecessary stops by the autonomous vehicle and a crash, we plotted the capture ratio (CR) and false positive ratio (FPR) profile.

The rest of the paper is organized as follows: In section 2, we provide additional details on the dataset, data manipulation, and statistical methods. In section 3, we present the results of our analysis and finally in section 4, we discuss what we learned.

2 Data and Methods

2.1 Data

We obtained our dataset from a previous study, known as the Integrated Vehicle-Based Safety Systems (IVBSS) study (Sayer et al., 2011). The data were collected from 108 licensed drivers in Michigan between April 2009 and April 2010. Sixteen late-model Honda Accords were fitted with cameras, recording devices, and a collision-warning system to collect visual and kinematic data from the drivers for a total of 40 days each: 12 days baseline period with systems switched off followed by 28 days with systems activated. We used the 12 days baseline unsupervised driving data for this analysis. Because information about road types and intersections outside Michigan were not available, we restricted our analysis to driving within Michigan to facilitate the accurate identification of an intersection and its associated road type. Accurate identification of an intersection allowed us to determine a reference time to start extracting the information necessary for this analysis.

In this study, we had data from 108 drivers who made 3,795 turns. Of these 3,795 turns, 1,823 were left turns. We took the time at which the vehicle was 100 m away from the center of an intersection to which it was heading as the reference point for the start of data extraction and stopped extraction at the time the vehicle was beyond the center of an intersection. We extracted both the speed of the vehicle (in m/s) and the amount of distance traveled (in m) at 10 ms intervals starting from our reference point. We also defined a vehicle as stopped when its speed was $\leq$ 1m/s.

2.2 Data manipulations

To create an algorithm that could be implemented, we first had to reference intersections by distance rather than time. To that end, we converted our time series of vehicle speeds to a distance series starting from -100 m away from the center of an intersection to -1 m away from the center of an intersection at every 1 m interval.

In addition to converting our time series to a distance series, we defined a distance-varying outcome. This was done because we were interested in the question “Will the human-driven vehicle stop in the future? ” at every meter away from the center of an intersection. An additional reason for defining a new distance-varying outcome was that we found turns where the vehicle stopped early. If we defined an overall outcome for each turn based on whether the vehicle stopped at any point during the whole turn maneuver, the prediction model would be influenced by behavior unrelated to decision-making related to the execution of the turn. Instead, we define “stopping in the future” at each point in time as referring only to future time points. In other words, the outcome is not a single value defined for the whole maneuver (the driver stopped at some point) but a variable value defined at each point.

Hence, to define the new distance-varying outcome, we employed the following notation. Let i be the i^{th} turn and j be the j^{th} meter away from the center of intersection, $j=-100,\ldots,-1$. Let s_{ij} be the new distance series of vehicle speed and y_{ij} be the distance-varying outcome (1=stopped in future, 0=will not stop in future) of the i^{th} turn at j be the j^{th}m. Then, we defined y_{ij} as follows:

1. If $s_{ij}>1m/s \ \forall \ j=-100,\ldots,-1$, then set $y_{ij}=0 \ \forall \ j$.

2. If $s_{ij}\leq 1m/s$ for some $j\in\{-100,\ldots,-1\}$, let $c\in\{-100,\ldots,-1\}$ be the index such that $\forall \ j>c$, $s_{ij}>1m/s$. We set $y_{i,-100}=y_{i,-99}=\ldots=y_{i,c}=1$ and $y_{i,c+1}=y_{i,c+2}=\ldots=y_{i,-1}=0$.

Point 1 means that if the new distance-series speed profile of a particular turn was more than 1m/s throughout, the distance-varying outcome would be set to 0 throughout. figures 1 and 2 clarify point 2. figure 1 corresponds to the new distance series of Driver 40 Trip 34 Turn 1. The horizontal line indicates 1m/s. We can see that for $j>-19$, the speed of the vehicle was more than 1m/s. Hence in figure 2, the distance-varying outcome y_{ij} is set to 0 for $j=-18,\ldots,-1$. On the other hand, because for $j=-100,\ldots,-19$, the speeds s_{ij} could be less than or equal to 1m/s, we set their distance-varying outcome to 1.

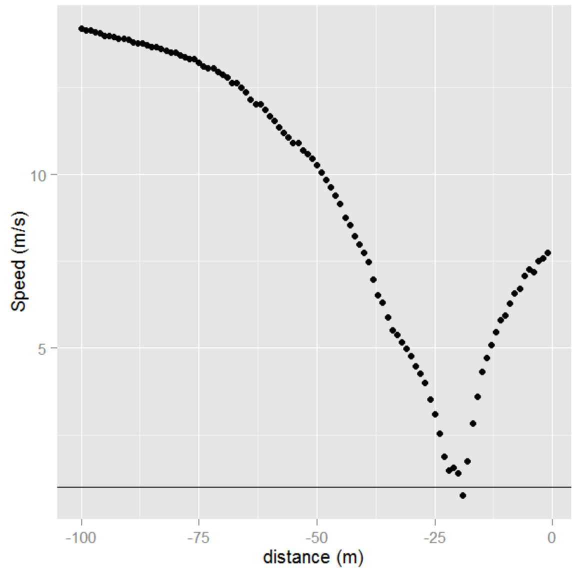

Figure 1: Example distance-series speed profile of Driver 40 Trip 34 Turn 1.

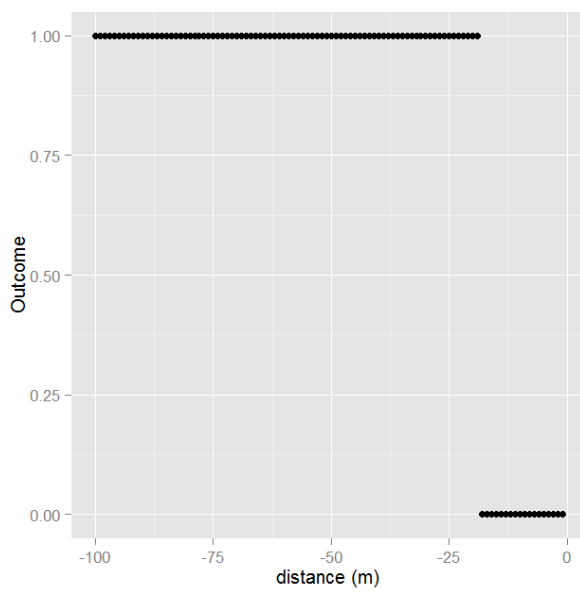

Figure 2: Distance-varying outcome for the speed profile of Driver 40 Trip 34 Turn 1.

2.3 Statistical methods

With the conversion and definition of the distance-varying outcome in place, we began developing our prediction model by first employing a moving window of speeds. This was done because, as the vehicle approached the center of the intersection, recent vehicle speeds contained information on whether a human driver will decide to stop. The full profile of a vehicle's past speeds may include this information as well, but they may also contain irrelevant information making the full profile of a vehicle's past speeds "noisier" compared with a window of recent speeds.

Next, we used Principal Components Analysis (PCA) on these windows to reduce the number of covariates in our prediction model. We found that the first three PCs explained at least 99% of the variation in speed regardless of the location of the moving window (See figure 3). Hence, the first three PCs were used as the predictors in our model.

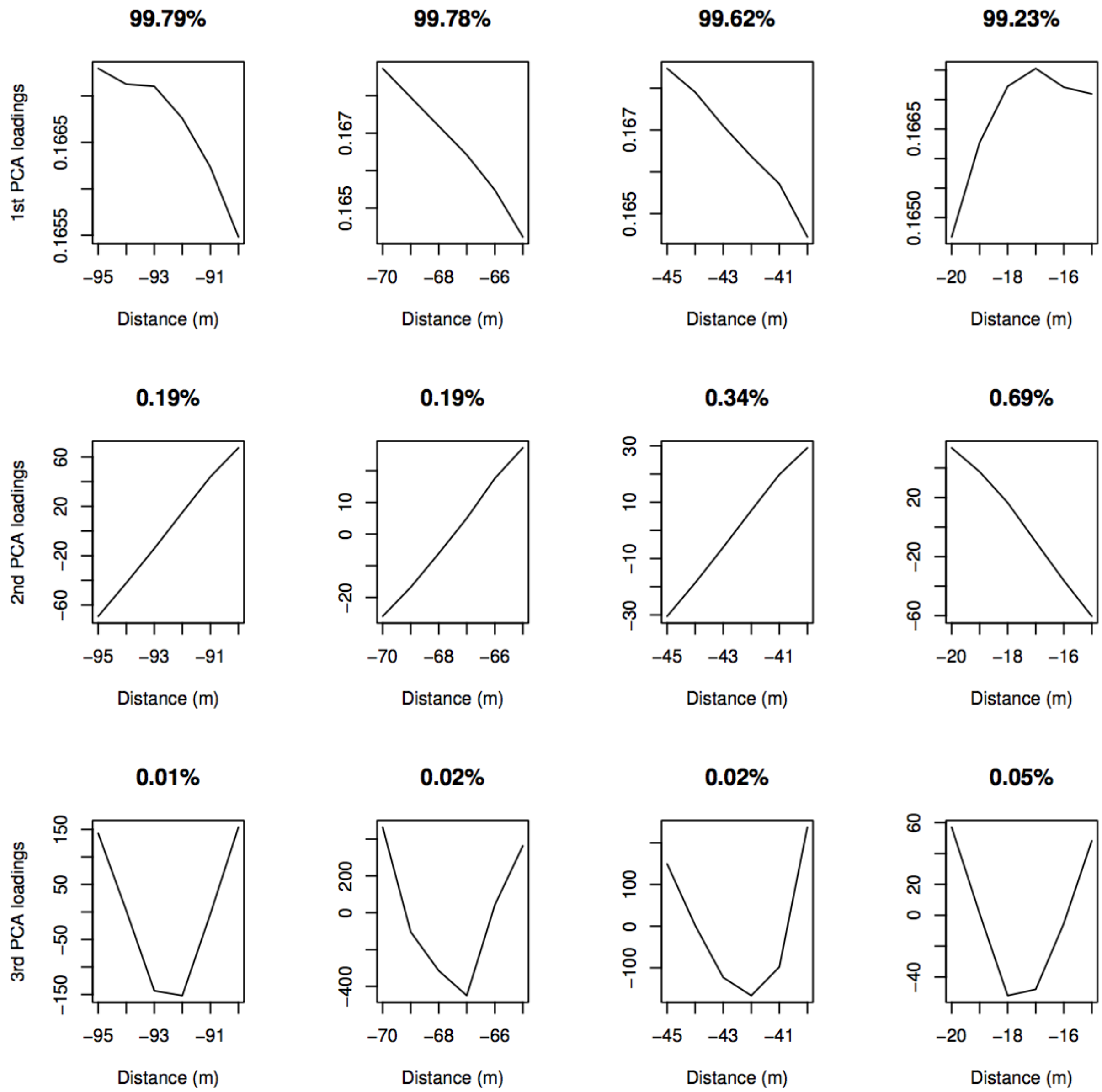

Figure 3: Principal Component loadings for the first, second, and third PC from -95m to -90m, -70m to -65m, -45m to -40m, and -20m to -15m (left to right).

To link our distance-varying outcomes to the first three PCs, we employed the BART model developed by Chipman et al. (2010). BART models the mean outcome (typically continuous) as a function of covariates by a sum of regression trees and incorporates the additive effects of predictors. Because we had binary outcomes, we needed to modify the BART formulation slightly. Following the recommendation of Chipman et al. (2010) , we linked our distance-varying outcome to BART using a probit model.

To evaluate our prediction model at every j^{th} meter away from the center of the intersection, we plotted the AUC value and its 95% confidence interval (CI) at every j^{th} meter. AUC calculates the proportion of observed outcomes that were ranked higher in terms of their predicted probability compared with the observed nonoutcomes. Thus, a value close to 1 indicates that the prediction model is performing much better than chance while a value close to 0.5 indicates that the prediction model performs no better than chance. We computed the CI of the AUC using the method of Hanley and McNeil (1982), which uses a linear approximation of the AUC to the Somer's D statistic to obtain an estimate of the variance of AUC.

In addition to the AUC, we plotted the profile of the Capture Ratio (CR), the y-axis of the Receiver Operating Characteristic (ROC) curve, the profile of the False Positive Ratio (FPR), and the x-axis of the ROC curve. For both profiles, we plotted them at nine different predicted probability cutoffs. Plotting the CR and FPR profile allowed us to find the optimal predicted probability cutoff that will balance the probability of an unnecessary stop by the autonomous vehicle and the probability of a crash between the autonomous vehicle and a human-driven vehicle.

3 Results

Our dataset contained 1,823 left turns: 894 of these turns started on major surface-road types, 613 started on minor surface roads, and 316 were started on local roads. Major surface-road types include roads supporting moderate travel within cities and quick travel between cities; minor surface roads include roads supporting moderate speed travel between neighborhoods. Local roads are defined as roads that support lower speed travel between neighborhoods. We also found 812 eventual stops defined as $s_{ij} \leq 1 m/s$ for some $j \in \{-100, \ldots, -1\}$. The average speed in all turns was 10.5 with a standard error of 4.2 and each driver took about 17 left turns (16.9, standard error 10.8). We determined the length of our moving window *w* by using a 10-fold cross validation AUC (cvAUC) with the first three PCs as the variables and BART as the prediction model. We compared the cvAUC profiles with *w* from 3 to 50. We chose a window length of 6 because the 10-fold cvAUC profile was higher compared with window lengths of 3, 4, and 5 from -95m to -30m. Similarly, for distances more than -30m, the cvAUC of window length 6 was more than that of window lengths 7, 8, 9, and 10.

Figure 3 shows the coefficients of the PCs allocated to the speeds from -95m to -90m, -70m to -65m, -45m to -40m, and -20m to -15m (left to right). Aside from the first three PCs explaining nearly 99% of the variation in the moving windows for all *j*, we also noted that the coefficient profile showed remarkable consistency throughout the approach to the center of intersection. The first PC is a form of average speed, and the second PC resembles a form of acceleration or deceleration.

Our BART model with *w*=6 and using the first three PCs as predictors produced fairly good AUC results (figure 4). The AUC profile together with its 95% CI were all above 0.7 throughout the left-turn maneuver. Our AUC profile was 0.75 at -95m away from the center of intersection and steadily increased to over 0.80 by -60m out. It reached 0.90 by -25m out, and increased to 1 as the vehicle approached the center of intersection.

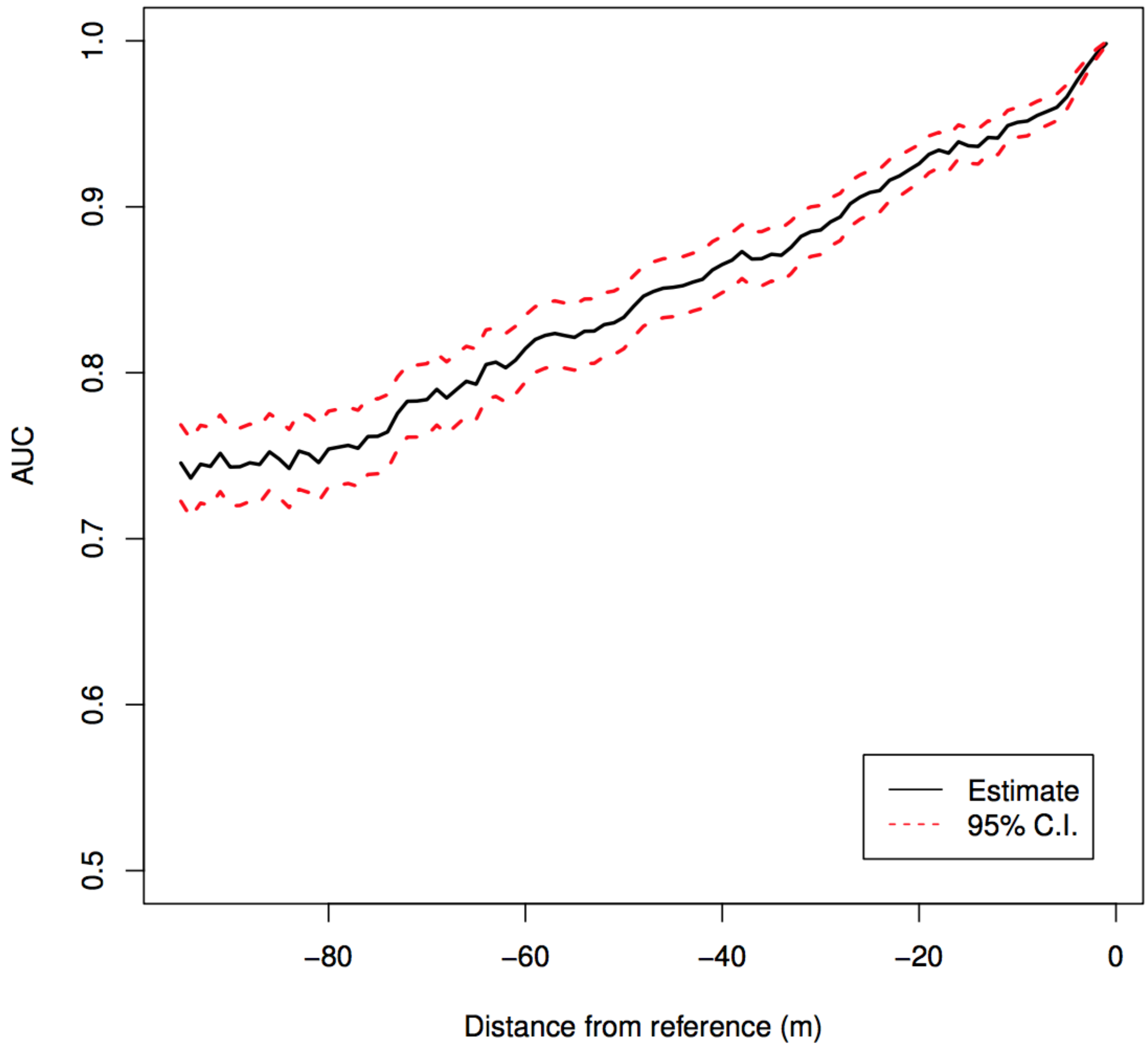

Figure 4: Area Under the receiver operating characteristic Curve (AUC) profile with 95% confidence interval (CI) of the BART prediction model.

Figure 5 shows the CR and FPR profiles under nine different predicted probability cutoffs, from 10% to 90% in 10% intervals. By a *x*% predicted probability cutoff, we mean that for any predicted probability produced by our BART prediction model, those that were more than *x*% were labeled as stops and those that were less than or equal to *x*% were labeled as nonstops. The CR then looks at the proportion of actual stops that were labeled correctly as stops and the FPR looks at the proportion of nonstops that were labeled incorrectly as stops. The solid lines in figure 5 represent the CR and are equivalent to the autonomous vehicle correctly predicting that the human-driven vehicle would stop using our BART model with the particular predicted probability cutoff. The dotted lines represent the FPR and are equivalent to the autonomous vehicle incorrectly predicting that the human-driven vehicle would stop. In this scenario, there would be risk of a crash if the autonomous vehicle assumed the human would stop and continued on a conflicting path.

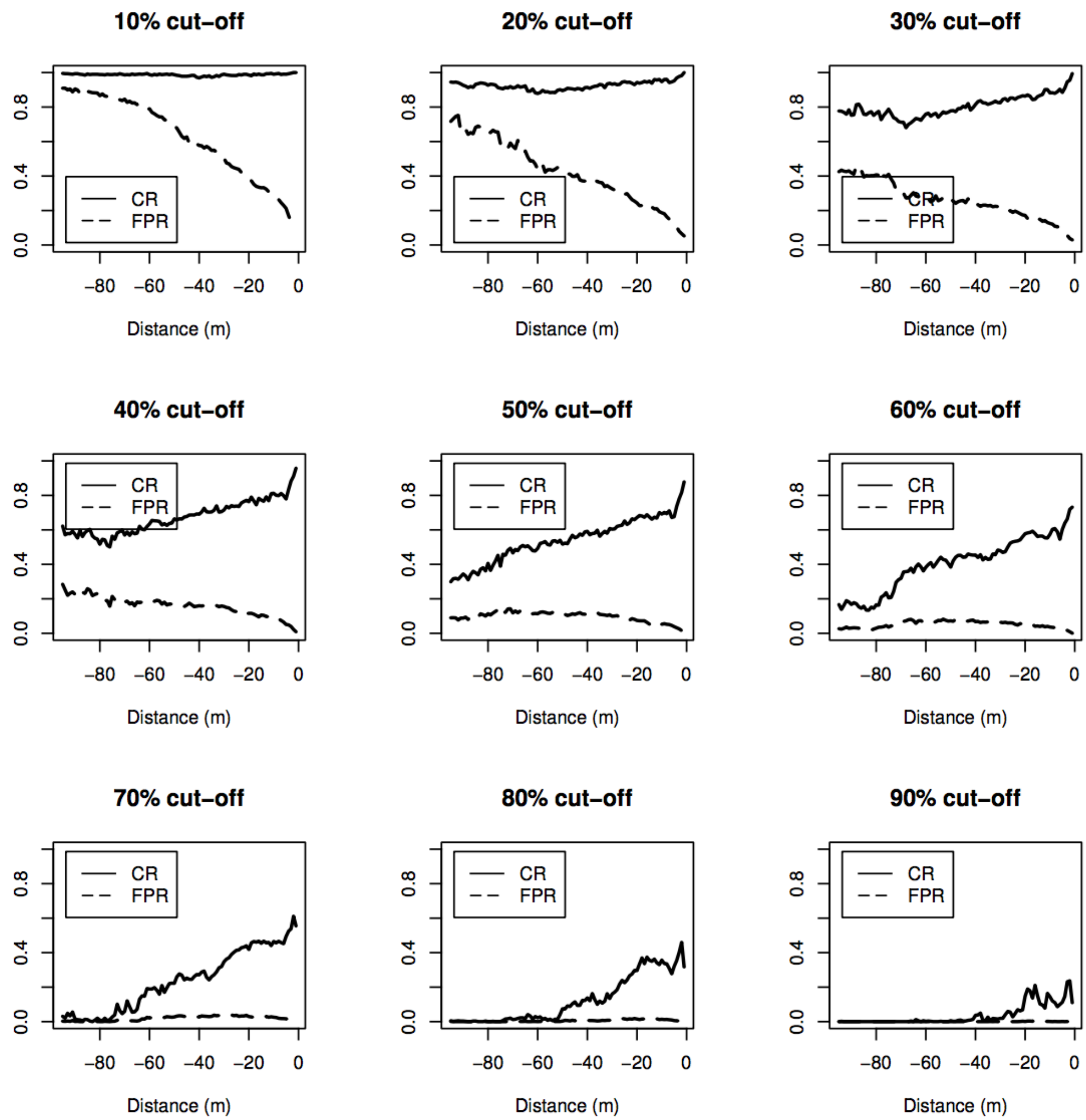

Figure 5: Capture Ratio (CR) and False Positive Ratio (FPR) profiles under nine different predicted probability cut-offs.

4 Discussion

In this study, we showed how we could use the kinematic behavior of speed from a human-driven vehicle to predict the human driver's decision of stopping before executing a left turn. We employed a moving window of vehicle speeds to capture relevant information for prediction and used PCA to reduce the number of variables in our model. We then employed a recently developed model, BART, to link our distance-varying outcome to the PC variables. Finally we evaluated our prediction model by plotting the AUC, CR, and FPR profiles.

Six meters of speed data at each j^{th} meter away from the center of intersection gave us good cvAUC performance both near to and far from the center of intersection. We used the first three PCs as the covariates in our prediction model because they explained at least 99% of the variation in the 6m window of speeds at each j^{th} meter. Our BART model produced an AUC of 0.75 at -95 m away from the center of intersection and this value increased steadily to 1 as the vehicle approaches the center of intersection.

We decided to use PCA as the method to reduce the number of variables in our model because of the surprising consistency we found in the profile of the PC coefficients (figure 3). We did not base our choice of the first three PCs as the variables in our model only on the amount of variation in explained. Since our ultimate goal was prediction, we investigated how much prediction performance would be added with the inclusion of the first five PCs in terms of AUC. We found large increases in the AUC profile when the first two PCs were added and a meaningful increase when the third PC was added. When the fourth and fifth PC were added, we found no improvement in the AUC profile. Moreover, when we plotted the PC values of the fourth PC and above, we found them to be inconsistent and difficult to interpret. We also considered using speed and acceleration in place of the first and second PC, given their resemblance to these quantities. However, we found that when we attempted this replacement, the resulting AUC profile was substantially lower compared to the AUC profile from using the PCs. Another alternative to using the first three PCs was the direct use of the 6m of speed as variables in the BART model. The rationale of this method was we can view the first three PCs as linear combinations of the 6 m of speed since $X_{j(q)}=M_j u(j)_{(q)}$. So the use of the first three PCs and the 6 m of speed data would produce similar results. In addition, PCA involves matrix multiplications, which could slow down computation when the number of observations increase. Unfortunately, this alternative method does not produce an AUC profile better or comparable to the AUC profile produced using the first three PCs. We suspect the reason is that PCA extracts useful information from the 6 m of speed data. And by using all the information from the 6 m of speed data, some noise may have been added.

We also considered many prediction models as alternatives to the BART model including the linear logistic regression model with the first three PCs as covariates, the non-linear logistic regression model using cubic splines with a knot at the mean of each of the three PCs, and the Super-Learner (van der Laan and Polley, 2010). The Super-Learner is an ensemble method that combines the prediction result of any machine learning to obtain a better prediction model. The AUC profile of the BART model was better compared to the linear and nonlinear logistic regression model. Although the AUC profile of the Super-Learner was somewhat better compared to BART, the improvement over BART Super-Learner produced was highly variable with various distances performing the same as BART. Therefore, we chose BART as our prediction model.

Although our BART model performed well in predicting a pre-left-turn stop, there is still room for improvement. First, we did not use other baseline covariates such as presence of a lead vehicle, distance from the center of intersection when a turn signal was first activated, and many others. Including these variables may improve the performance of our prediction model further away from the center of intersection. We were less concerned about the performance near the center of intersection since the AUC of our model was already close to 1. We intend to investigate which covariates should be included to improve performance by using the BART variable-selection method proposed in Bleich et al. (2014). A point to note here is that the inclusion of variables such as the gender and age of the driver may not be practical because it is unlikely that the sensors equipped on an autonomous vehicle would be able to capture such information.

Second, we are aware that our naturalistic driving data were collected from the same drivers traveling on similar road types multiple times. This implies that our assumption that each turn is independent from the other may be violated since there could be some form of intradriver or intraroad type correlation between turns. We believe this can be solved by extending the BART model to include a random intercept. Preliminary results by stratification showed promise, and we are currently working on implementing a random intercept BART model to our data.

Finally, on closer inspection of our nine different CR and FPR profile plots, we can see that different predicted probability cutoffs could be proposed at different distances instead of one overall cutoff. This implies that different decisions could be made at different distances depending on the cost we decide to allocate to either, correctly predicting a driver stop and hence avoiding unnecessary stops in the autonomous vehicle, or incorrectly predicting a driver stop and hence resulting in a crash with the human-driven vehicle. To obtain the different optimal cutoffs that would balance the CR and FPR at each distance, we suggest attaching different costs to the CR and FPR at each j and then employing numerical methods to solve for the optimal cutoff.

5 Recommendations

The goal of this project was to use statistical prediction methods to tie ongoing kinematic behavior to a near-future decision made by a driver. A good prediction model operating in real time could provide much-needed information about human drivers' decisions to help inform the operation of nearby automated vehicles.

The prediction performance of our model with no other information than speed was good enough to suggest that this approach has real promise. We expect that additional information, especially about the location of any oncoming vehicle, will improve prediction, especially close to the intersection.

We recommend further work to improve the model with better methods (especially taking account of within-driver variability) and additional predictors (especially the proximity of oncoming vehicles). In addition, a next step should build a feedback loop into the model to simulate the way in which the behavior of the automated (oncoming) vehicle might alter the behavior of the human-driven vehicle.

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