Report #20-UT-080

NSTSCE

National Surface Transportation Safety Center for Excellence

Modeling Driver Intent in Potential Right Turning Scenarios

Thomas Gorman

Submitted: April 20, 2020

Technology | Impairment | Mobility | Infrastructure

Housed at the Virginia Tech Transportation Institute
3500 Transportation Research Plaza • Blacksburg, Virginia 24061

ACKNOWLEDGMENTS

The authors of this report would like to acknowledge the support of the stakeholders of the National Surface Transportation Safety Center for Excellence (NSTSCE): Tom Dingus from the Virginia Tech Transportation Institute; John Capp from General Motors Corporation; Chris Hayes from Travelers Insurance; Terri Hallquist and Nicole Michel from the Federal Motor Carrier Safety Administration; Cathy McGhee from the Virginia Department of Transportation and the Virginia Transportation Research Council; and Jane Terry from the National Safety Council.

The NSTSCE stakeholders have jointly funded this research for the purpose of developing and disseminating advanced transportation safety techniques and innovations.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS AND SYMBOLS

ADS	automated driving system
AV	automated vehicle
DAS	data acquisition system
GPS	Global Positioning System
NDS	naturalistic driving study
ROC	receiver operating characteristics
SHRP 2	Second Strategic Highway Research Program
VTTI	Virginia Tech Transportation Institute

CHAPTER 1. INTRODUCTION

Human drivers can assess a situation and predict the maneuvers of other road users. This important skill enables drivers to maintain safety and rider comfort while driving. In some scenarios, this skill could also help boost fuel economy and reduce commute time and congestion. It would be beneficial for automated driving systems (ADS) to be encoded with this capability, enabling the same benefits to be realized by automated vehicles (AVs). This encoded capability could take shape in the form of a statistical model that predicts the future decisions and states of other road users.

Of the many scenarios in which predicting decisions of other road users could be beneficial to an AV, this study focuses on the scenario shown in Figure 1 in which a vehicle is traveling on a two-lane undivided highway and is approaching a side road on the right. There are three situations where an AV would benefit from being able to accurately predict if the vehicle will turn right or go straight through the T-intersection via a model of driver intent:

- Situation A – A lead vehicle ahead of the AV approaches the intersection and can either turn or go straight (Figure 2).

- Situation B – A vehicle on the highway is approaching the intersection while the AV waits to turn onto the highway (Figure 3).

- Situation C – A Level 1 vehicle under manual control on the highway approaches the T-intersection where a potential conflict is present (Figure 4).

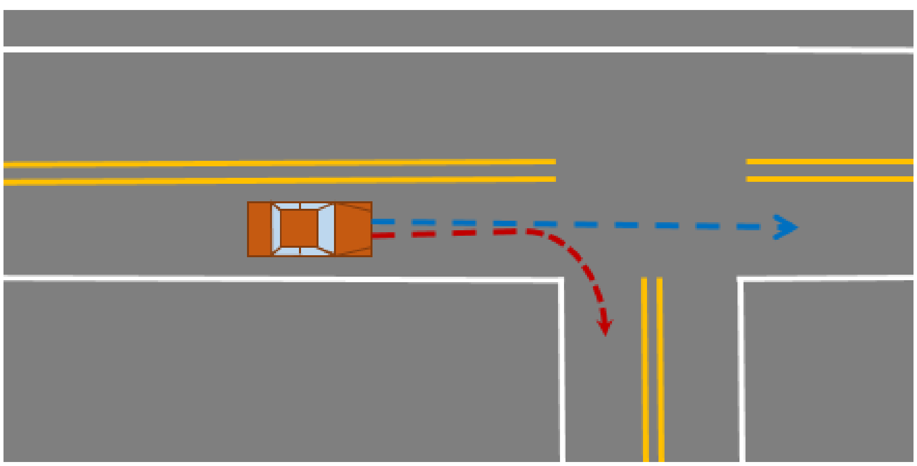

Figure 1. Diagram. This study aims to create a model that predicts if vehicles will go straight or turn right at T-intersections

SITUATION A

Consider the situation in which an AV is following a lead vehicle as both vehicles approach a side road on the right as shown in Figure 2. The AV can sense the location, speed, and acceleration of the lead vehicle via a line-of-sight system (e.g., radar, lidar) or a connected vehicle technology.

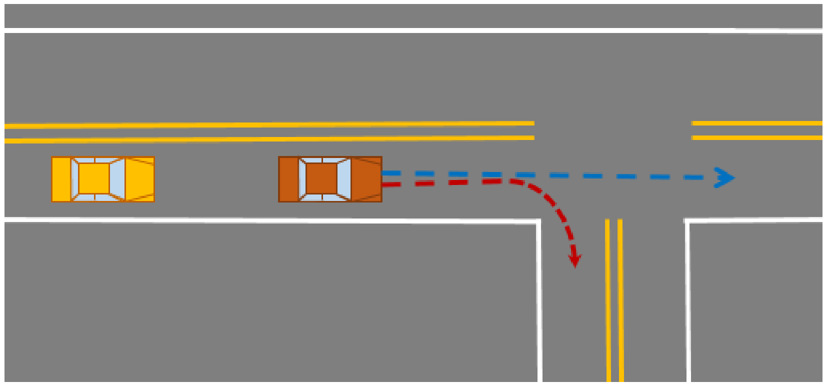

Figure 2. Diagram. An AV (orange) is attempting to predict if the lead vehicle (red) will turn right or go straight through the T-intersection.

As summarized in Table 1, accurately predicting the intent of the lead vehicle's operator could have positive consequences for the AV, such as the prevention of a crash or improved fuel efficiency. On the other hand, incorrectly predicting the operator's intent could lead to a crash.

Table 1. Consequences of accurate and inaccurate predictions for both actions of a lead vehicle approaching a side road.

	Lead Vehicle Goes Straight	**Lead Vehicle Turns**
Model Predicts Straight	• Maintain appropriate headway	• Hard braking could occur • Crash could occur
Model Predicts Turning	• Annoyance • Could detract from user trust	• Prevent rear-end crash • Maintain smooth ride and rider comfort • Improve fuel efficiency

SITUATION B

Consider the situation depicted in Figure 3 in which an AV is waiting at a T-intersection to turn onto the main road as a vehicle approaches from the left. The AV can sense the location, speed, and acceleration of the approaching vehicle via a line-of-sight system (e.g., radar, lidar) or a connected vehicle technology.

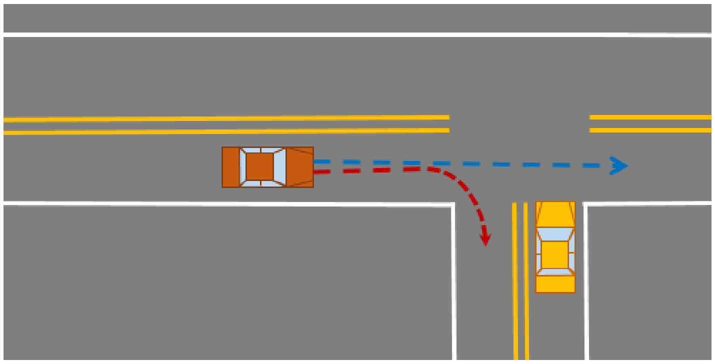

Figure 3. Diagram. An AV (orange) is attempting to predict if a vehicle (red) approaching from the left will turn right or go straight.

As summarized in Table 2, accurately predicting the intent of the oncoming vehicle could lead to the prevention of a potential conflict or reduce commute time. An inaccurate prediction that the oncoming vehicle will turn right could lead to a crash. If the ADS inaccurately predicts that the oncoming vehicle will go straight, this could lead to rider annoyance or driver annoyance for Level 1 or 2 systems.

Table 2. Consequences of accurate and inaccurate predictions made by an AV in Situation B.

	Approaching Vehicle Goes Straight	**Approaching Vehicle Turns**
Model Predicts Straight	• Prevent potential conflict	• Annoyance • Could detract from user trust
Model Predicts Turning	• Could lead to crash • Crash not prevented (Level 1 automation)	• AV can safely proceed • Reduce commute time

SITUATION C

The third applicable situation applies only to Level 1 AVs. Consider the situation depicted in Figure 4 in which a Level 1 AV is approaching a side road. There exists a conflict just beyond the potential turning point, for example, a vehicle turning onto the main road from the side road. The human driver is in control of the AV and the ADS is attempting to predict if the driver will go straight or turn right.

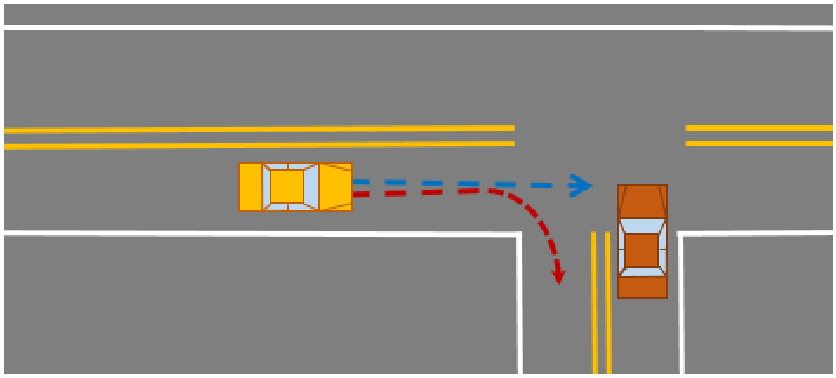

Figure 4. Diagram. A Level 1 AV is attempting to predict if its driver will turn right or go straight at a T-intersection that another vehicle is entering from the side road.

Table 3 summarizes the potential consequences of accurate and inaccurate predictions made by the ADS in Situation C. If the system accurately predicts the driver will turn right, it will not perform an undesirable avoidance maneuver.

Table 3. Consequences of accurate and inaccurate predictions made by an AV in Situation C.

	AV Driver Goes Straight	**AV Driver Turns**
Model Predicts Straight	• Prevent conflict	• Annoyance • Could detract from user trust
Model Predicts Turning	• Conflict not prevented	• No action required from or performed by ADS

CHAPTER 2. OBJECTIVE

This study aims to build predictive models of driver intent when approaching side roads on the right as shown in Figure 1. Specifically, the objective of this study is to create a series of models that predict, at decrementing distances from a T-intersection, if a vehicle will turn right or go straight.

CHAPTER 3. METHODS

DATA SETS

Second Strategic Highway Research Program

The Second Strategic Highway Research Program (SHRP 2) Naturalistic Driving Study (NDS) is the largest naturalistic driving study that has been undertaken to date. The SHRP 2 database consists of over 5.5 million trips driven by 3,542 drivers across six collection sites (see Figure 5) in the continental United States.

Figure 5. Map. SHRP 2 data collection sites.

The Virginia Tech Transportation Institute (VTTI) developed a data acquisition system (DAS) to support the research questions and objectives of the SHRP 2 NDS program, which included compiling a data set that could be used to support future data mining activities such as this one. The DAS facilitated the collection of the following data of interest to this study:

- Host vehicle speed data
- Geographic Positioning System (GPS) data
- Accelerometer data
- Brake activation status

Map Database

This study used Here.com digital map data of travel networks. The map data generally include links that join at nodes representing intersections. This study relied on previous work conducted by VTTI that matched SHRP 2 GPS records to digital map data (McLaughlin, 2015).

DATA PROCESSING

Figure 6 shows the data processing workflow used to conduct the analysis for this study.

Figure 6. Diagram. Data processing workflow.

Intersection Identification

Given the interest in three-way intersections, the first step in identifying candidate intersections was to search for nodes in the Here.com database to which three links (road segments) were attached. By computing the angles between the three links, approximate 180-degree and 90-degree angles (±15 degrees) were used as thresholds to select only T-intersections.

In order to build accurate models of driver intent, it was necessary to identify intersections that were frequently traversed by SHRP 2 drivers. Using map-matching data (McLaughlin, 2015), the intersections of interest were further restricted by the following criteria:

- There were at least 150 SHRP 2 traversals from Point A to Point B (see Figure 7).
- There were at least 150 SHRP 2 traversals from Point A to Point C (see Figure 7).

For this preliminary analysis, intersections were further restricted to two-lane undivided highways and roads.

In order to limit the amount of computing time, this study selected 10 intersections for modeling purposes and two intersections for testing the models.

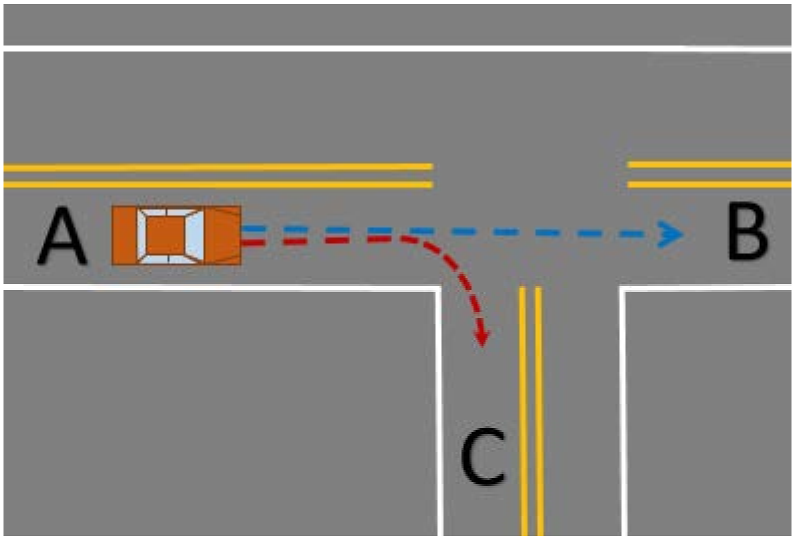

Figure 7. Diagram. This study focused on scenarios occurring at T-intersections on two-lane undivided highways.

Vehicle Trajectory Identification and Classification

For each intersection selected for this study, the three links were classified as A, B, or C (see Figure 7) based on the angles between each of them. An algorithm searched across all SHRP 2 trips to identify traversals of links in this orientation, in two traversal sequences. Traversals that passed through Link A directly followed by Link B were classified as “straight” maneuvers. Traversals that passed through Link A directly followed by Link C were classified as “right turn” maneuvers.

Data Cleaning

Although using map-matching data yielded mostly valid traversals, some flagged traversals were anomalous. For example, sometimes trajectories of vehicles traveling under a bridge were identified as traveling over the bridge. For other traversals, the trajectory was misclassified as turning right when the vehicle traveled straight through the intersection. An additional traversal identification step was applied that tested for trajectories that passed through points before and after the intersection, rejecting those that did not follow the sequence needed to support this work.

Figure 8 shows an example for data extracted for an intersection analyzed in this study. The plot on the left shows host vehicle speed as a function of the vehicle’s distance from the intersection. Red traces represent vehicles that turned right at the intersection. Blue traces represent vehicles that traveled straight through the intersection. The image on the right shows satellite imagery of the intersection with trajectories overlaid. The red trajectories correspond to the red traces in the left plot. The blue trajectories correspond the blue traces in the left plot. The green trajectories are continuations of the blue trajectories beyond 10 meters prior to the intersection. The magenta trajectories are continuations of the red trajectories beyond 10 meters prior to the intersection.

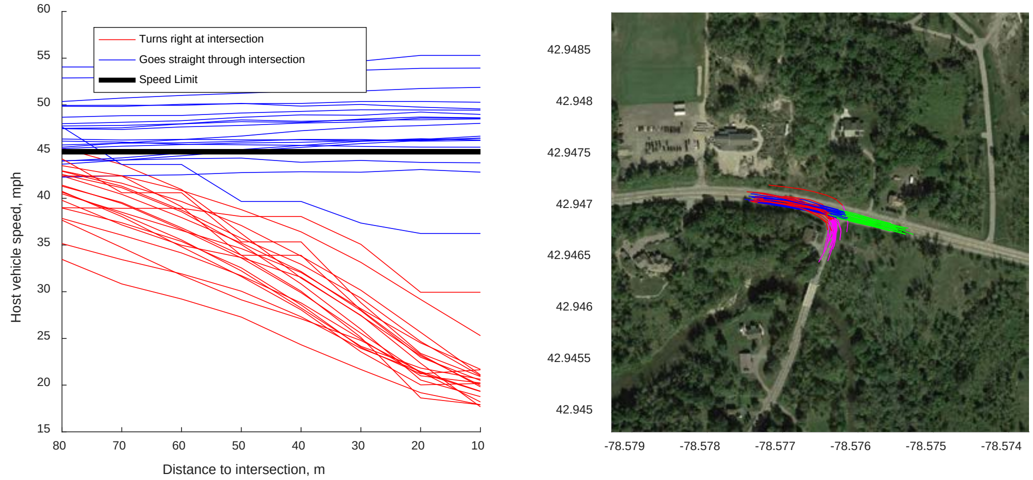

Figure 8. Graphs. Host vehicle speed and satellite map with trajectories for a selected T-intersection with speed limit of 45 mph.

Figure 9 shows another example for data extracted for an intersection analyzed in this study. At this intersection, the main road has a speed limit of 30 mph.

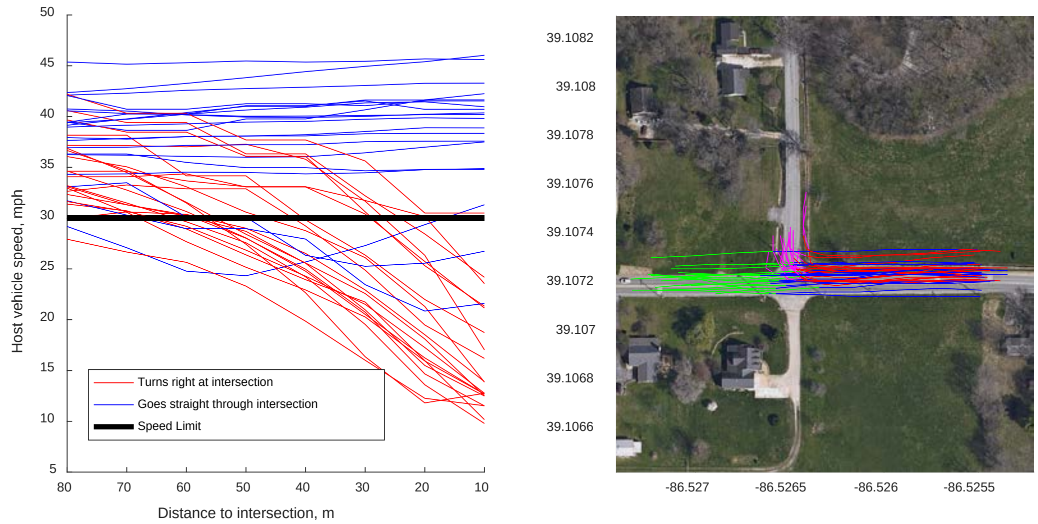

Figure 9. Graphs. Host vehicle speed and satellite map with trajectories for a selected T-intersection with speed limit of 30 mph.

Figure 10 shows vehicle longitudinal acceleration plotted against distance to intersection for one of the intersections analyzed in this study.

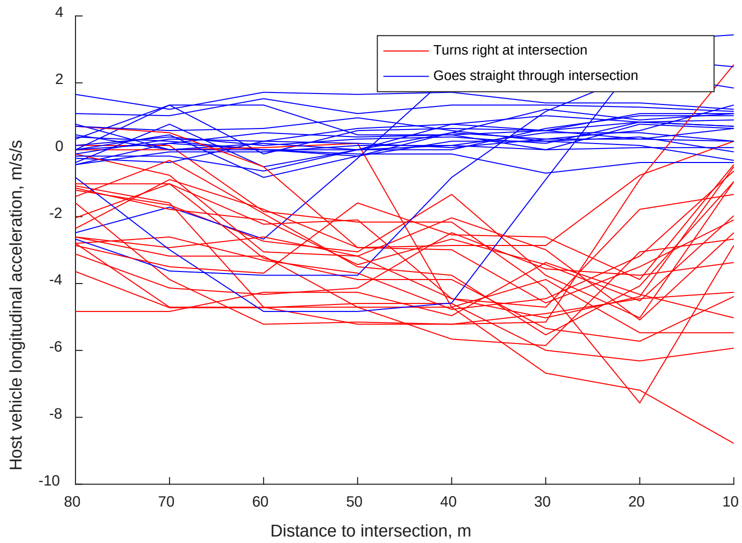

Figure 10. Graph. Host vehicle longitudinal acceleration against distance to one of the intersections selected for analysis.

A total of 9,363 (3,164 right turning and 6,199 straight) trajectories were selected for model training and validation. A total of 1,509 (696 right turning and 813 straight) trajectories were selected for model testing.

Feature Extraction

As stated in the objective, this study aims to develop a series of predictive models of driver intent at various distances from the intersection. The selected distances of interest are 10 meters to 70 meters from the intersection at increments of 10 meters, yielding a total of seven sets of features. These distances were selected to model a realistic range in which an AV might activate in response to a prediction. For each distance *D*, the following features were extracted as candidates for modeling intent:

- Vehicle speed at *D*
- Vehicle speed at *D* + 10 m
- Vehicle longitudinal acceleration at *D*
- Vehicle longitudinal acceleration at *D* + 10 m
- Vehicle lateral acceleration at *D*
- Vehicle lateral acceleration at *D* + 10 m
- Vehicle brake pedal state at *D*
- Vehicle brake pedal state at *D* + 10 m
- Vehicle speed/speed limit at *D*
- Vehicle speed/speed limit at *D* + 10 m
- Speed limit

Behavior modeling

For each of the seven sets of features, a logistic regression was used to model the driver intention to turn right or go straight through the intersection. Parameters were selected as significant via the Lasso with 10-fold cross validation. This method utilized all the training data set for both parameter selection and model validation. The test data set was used for model testing, which is presented in the Results section.

CHAPTER 4. RESULTS AND DISCUSSION

The objective of this work was to build predictive models of driver intent at T-intersections given the vehicle speed, acceleration, brake pedal state, and speed limit. The generated models predict if the driver will go straight or turn right at the intersection. Appendix A shows the results of modeling driver intent via logistic regression. With the exception of vehicle speed at D + 10 meters, all of the variables were significant at multiple distances from the intersection.

Figure 11 shows receiver operator characteristic (ROC) curves for the series of predictive models that were developed in this study. A true positive is defined as an instance in which the model accurately predicts that the vehicle will turn right. A true negative is defined as an instance in which the model accurately predicts that the vehicle will go straight. A false positive occurs when the model predicts turning and the vehicle actually goes straight. A false negative occurs when the model predicts the vehicle will go straight and the vehicle actually turns right. As the distance between the vehicle and intersection closes, the selected parameters become more predictive of driver intent.

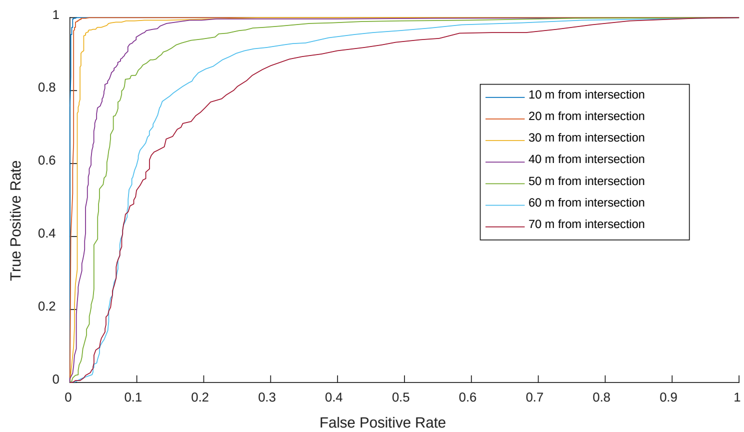

Figure 11. Graph. The test data set was used to generate ROC curves for the series of models.

By setting the discrimination threshold to 0.5, we can more clearly see how the true positive and false positive rates vary with distance between the vehicle and intersection. Figure 12 shows that both the sensitivity and specificity increase as the vehicle approaches the intersection.

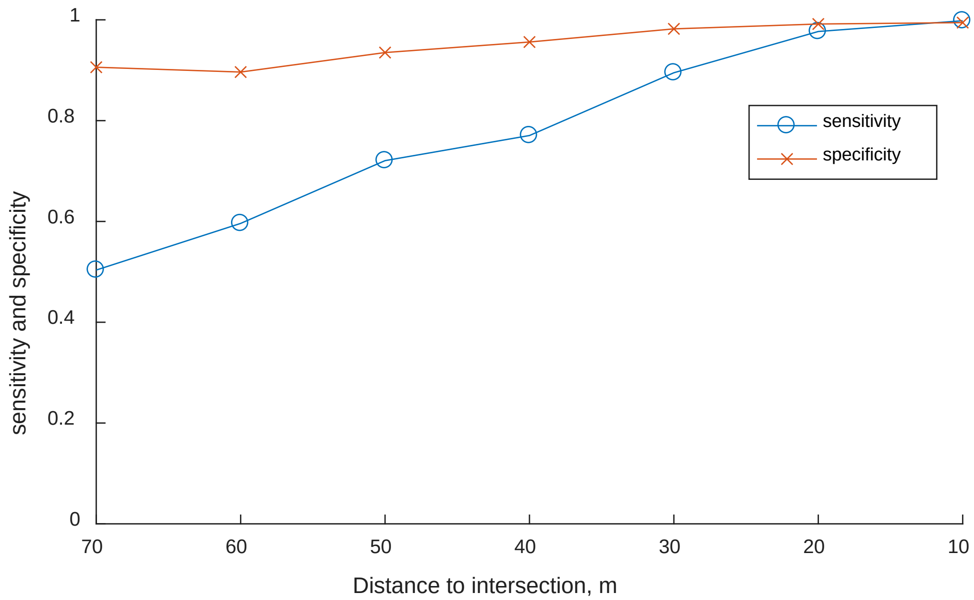

Figure 12. Graph. Both the sensitivity and specificity of the models increase as the vehicle approaches the intersection.

Depending on the scenario, the sensitivity and specificity for a given model have different implications. For the purpose of demonstration, let us momentarily assume that an AV would completely trust the binary output of the models developed in this study in order to make a decision. For Situation A outlined in the Introduction, a low sensitivity would result in more frequent crashes, and a low specificity would result in more frequent driver annoyance. For situations B and C outlined in the Introduction, a low sensitivity would result in more frequent driver annoyance, and a low specificity would result in more frequent crashes. It is beneficial that the models developed in this study have the utility to be applied to three different scenarios, but designers of ADS need to choose appropriate discrimination thresholds for each scenario.

CHAPTER 5. CONCLUSIONS

This is the first study to use SHRP 2 data to build statistical models that predict if a driver will go straight or turn right at a T-intersection. The models show promise in predictive ability and could be incorporated into an ADS to help inform the system when more conservative driving might be beneficial. However, the derived models should not be used as the only source for safety decision-making because the risk of a crash would be too high. Future work is required to boost the predictive power of these models, which could eventually make them more reliable for decision-making in safety-critical situations.

Ideas for future work to boost predictive power include the following:

- Selecting a larger sample size for modeling purposes
- Extending the logistic regression model to a mixed-effects model
- Exploring other machine learning techniques for modeling intent

In addition to future work to improve the models generated in this study, there exists a need for predictive models for many other scenarios that AVs may encounter.

APPENDIX A. MODEL PARAMETERS

Distance to Intersection	70 m	60 m	50 m	40 m	30 m	20 m	10 m
Intercept	21.38902	25.52472	30.05277	30.85858	1.031826	-5.58443	-23.4679
Coefficient for vehicle speed at D	-95.4137	-24.7262	-27.5262	-13.1102	-15.9129	-12.3501	-7.7041
Coefficient for vehicle speed at D + 10 m	54.19406	0	0	0	0	0	0
Coefficient for vehicle longitudinal acceleration at D	-47.2141	-49.5698	-48.6813	-62.8352	-67.7732	-66.4969	-37.9368
Coefficient for vehicle longitudinal acceleration at D + 10 m	-4.41104	-2.92111	-3.96018	-3.79518	-5.77405	0	-1.5323
Coefficient for vehicle lateral acceleration at D	9.575895	-1.30734	0	23.0922	62.5802	33.54182	43.41591
Coefficient for vehicle lateral acceleration at D + 10 m	10.04052	17.01302	9.219463	0	9.881534	42.80863	32.25324
Coefficient for vehicle brake pedal state at D	1.545771	1.67609	1.337961	0.88112	0.433887	0	0
Coefficient for vehicle brake pedal state at D + 10 m	-0.6384	-0.72273	-0.21977	-0.01799	0.069136	0	-0.22566
Coefficient for vehicle speed/speed limit at D	71.30227	0	0	0	0	-7.54904	-10.563
Coefficient for vehicle speed/speed limit at D + 10 m	-43.1736	12.23825	14.05369	0	0	0	0
Coefficient for Speed limit	11.23452	5.916257	6.362608	1.815951	1.611176	0	0

REFERENCES

McLaughlin, S. (2015). *Matching GPS Records to Digital Map Data: Algorithm Overview and Application* (15-UT-033). Blacksburg, VA: National Surface Transportation Safety Center for Excellence.