ON EN-ROUTE DIVERSION BEHAVIOR: EMERGING DATA COLLECTION TECHNIQUES AND MODELING METHOD

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1. ABSTRACT

Intelligent Transportation Systems (ITS) require more accurate and abundant data sources. One example is the implementation of Dynamic Message Signs (DMS) for the purpose of diverting drivers in order to mitigate congestion. This paper discusses the methods for modeling and calibrating drivers' en-route route changing decision with behavior data collected from emerging data collection techniques including laboratory driving simulators and field blue-tooth detectors. The behavior models are not based on assumptions of perfect rationality. Instead a novel descriptive approach based on naïve Bayes rules is proposed and demonstrated. The en-route diversion model is first estimated with behavior data from a driving simulator. Subsequently, the model is re-calibrated for Maryland based on blue-tooth detector data, and applied to analyze two dynamic message sign (DMS) scenarios on I-95 and I-895. This calibration method allows researchers and practitioners to transfer the en-route diversion model to other regions based on local observations. Future research can integrated this en-route diversion model with microscopic traffic simulators, dynamic traffic assignment models, and/or activity/agent-based travel demand models for various traffic operations and transportation planning applications.

2. BACKGROUND

Drivers' en-route route choice under information provision has been traditionally modeled by the econometric theory of random utility maximization (Ben-Akiva and Lerman 1985). Mahmassani and Liu (1999) adopted a multinomial probit framework to model the commuters' joint pre-trip departure time and en-route diversion behavior in response to real-time information, based on data from a laboratory interactive driving simulator. The study suggests that commuters switch routes if the expected travel time savings exceed an indifference band which varies with the remaining trip time to destination. Abdel-Aty et al. (1997) developed logit models to capture the effect of real-time information on en-route diversion using stated preference data. Khattack et al. (1995) estimated a bivariate ordinal probit model of drivers' diversion and departure time choice when traffic information is available.

Limitations exist in the en-route diversion models. First of all, they are often not well-calibrated due to data limitation and other issues. The inherent bias of the stated preference data and driving simulator data has long been argued as a major deficiency of the models (Bonsall and Parry 1991). Koutsopoulos et al. (1994) further assert that driving simulators for en-route diversion analysis can be more useful if revealed preference data collected from "actual en-route route choice behavior" and an appropriated designed calibration become available.

Moreover, unlike the decisions of departure time and pre-trip route choice, en-route diversion is a decision triggered by impulsion. When making en-route diversion decisions, a driver usually has very limited reaction time to obtain the real-time traffic information from the sources, process the information, compare the original route and the diverting route, and reach a decision. Therefore, some researchers (Arentze and Timmermans, 2007, Paz and Peeta, 2009) emphasize the need for rule-based computational process models, since it is claimed that utility-maximizing models do not always reflect the true behavioral mechanisms underlying travel decisions (people may reason more in terms of "if-then" structures than in terms of utility maximizing decisions). ALBATROSS applies CHAID decision trees to model the activity scheduling behavior (Ettema et al. 2005). Janssens et al. (2006) develops a Bayesian network augmented tree (BNT) approach to look at multi-facet decision making processes. This approach takes advantage of both Bayesian network and decision tree/rule induction method. Paz and

Peeta (2009) employ aggregate behavioral if-then rules and calibrate a weight vectors for these rules so as to match the estimated and actually observed network states.

3. RESEARCH OBJECTIVE

Other than rules that give only a simple classification, models that give probability estimates are favored in the field of practical data mining and artificial intelligence for their flexibility in applications of combining decisions and sensitivity analysis (Bourlard and Morgan 1990;Duda et al. 2001;Bennett 2003). Naïve Bayes model is one of the most efficient and effective algorithms that predict probability estimates. Although its underlying conditional independence assumption is rarely true in real-world applications, the correlation among variables does not affect the performance optimality of naïve Bayes model, as quantitatively proved by Zhang (2004). Few travel behavior studies have explored this promising approach except some research in mode choice modeling (Wu et al. 2011;Biagioni et al. 2009).

Following this line of research, the paper develops a naïve Bayes classifier to model drivers' en-route diversion behavior. And then a Bayesian approach to calibrating the Naïve Bayes model is developed to transform the naïve Bayes prediction into more accurate estimates. This calibration approach is practical-oriented and is demonstrated on a real-world en-route diversion case study where the Bluetooth-based testing dataset is collected. The main contribution of the paper lies in the originality of the model and calibration in en-route diversion behavior.

The remainder of the paper is organized as follows. Section 2 presents the training dataset, as well as the model development. Section 3 presents the testing dataset and the Bayesian calibration process. Conclusions and discussions on future research are offered at the end of this paper.

4. DATA COLLECTION

Training Data

The data for developing the en-route diversion classifier is the Massachusetts Driving Simulator Experiment Data (see Tian *et al.*, 2012 for more details about the data). 63 effective subjects were recruited in this driving simulator survey. There are three types of maps in the tests, shown in Figure 1. And each type of the maps appeared six times with randomly assigned travel times. Some social demographic information (i.e. gender, age, and years holding a driver's license) has also been collected.

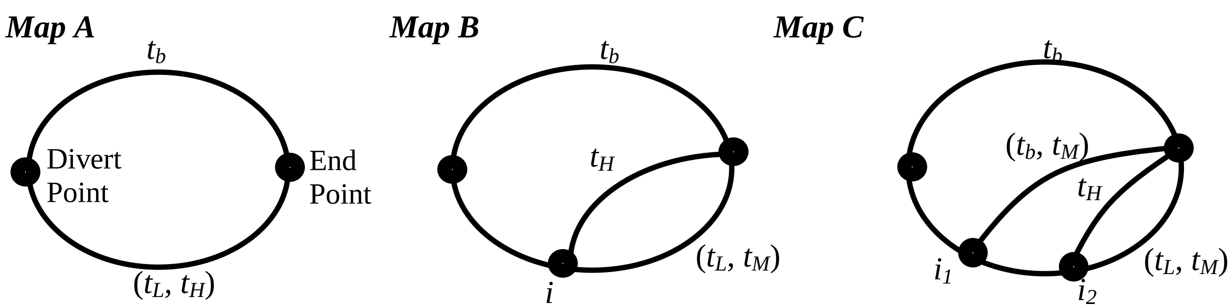

FIGURE 1: Three Types of Maps in the Driving Simulator Survey

In Figure 1, each map contains one routine route with deterministic travel time t_b and one risky diverting route using (m, n) to denote a random travel time. The risky branch gets more complicated in topology from Map A through C. Map A contains one simple diversion, with a possible low travel time t_L and high travel time t_H. In Map B, a bifurcation is added to the diverting route, where the safe detour has a deterministic travel time t_H. The risky Route has a low travel time t_L and a prohibitively long delay t_M, which could be due to an incident. At Node i, a subject will receive real-time information on the realization of the travel time on the diverting route. Map C adds another bifurcation to the diverting route, upstream of the one in Map B, with two possible outcomes t_b and t_M. Real-time information is available at Node i_1 and i_2 on the realized travel time. Similarly the information at either node could help drivers avoid the extremely high travel time t_M on the diverting route. And a driver, while driving, takes into account the real-time traffic information to some extent in making en-route diversion choice at the Divert Point.

Testing Dataset

As shown in Figure 2, I-95 and I-895 are two alternative routes that pass through the tunnels under the Baltimore Harbor and eventually rejoin at the East Baltimore. They split approximately five miles prior to the Baltimore City. The DMS device is installed prior to the split and is often used for displaying actual travel time, delay, and diversion messages regarding these two alternative routes (Hamedi et al. 2011). A number of Bluetooth sensors are deployed along these two routes to detect the actual travel time as well as the en-route diversion behavior (Haghani et al. 2010), as shown in Figure 2.

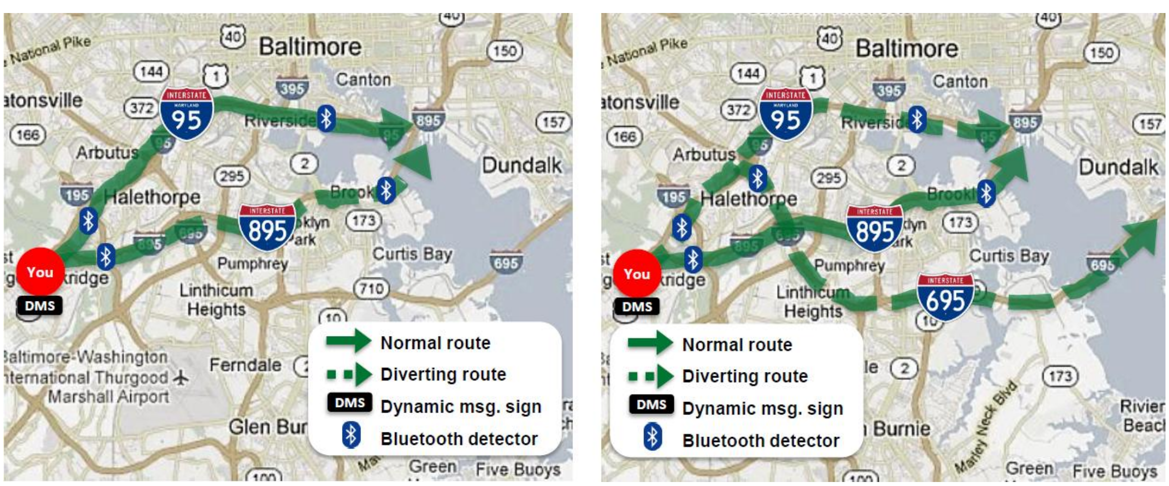

FIGURE 2: I-95/I-895 En-Route Diversion Scenarios and Sensor Locations

While enormous traffic-related ground truth information is collected during the two-week Bluetooth sampling period, two real-world en-route diversion scenarios are observed and extracted for the analysis. Scenario 1 is shown in the left graph in Figure 2. In this case, the DMS device posted travel time messages about the congestion on I-95 and suggested drivers to divert to I-895. Scenario 2 is shown in the right graph, where the DMS device reported major delay on I-895 and diverted drivers to I-95/I-695 corridor. The date, duration, and traffic diversion rate of these two scenarios are reported in Table 1.

TABLE 1: En-Route Diversion Percentage between I-95 and I-895

Scenarios	DMS and Date	DMS Duration	Average I-95 Percentage (%)	Average I-895 Percentage (%)	Standard Deviation
Scenario 1	Divert to I-895 3/31/2011; 4/6/2011	3/31: 16:50~17:16; 4/6: 9:48~10:04 10:07~10:21 16:05~16:21	78.5	21.5	12.03
Scenario 2	Divert to I-95 4/2/2011	7:31~7:46 9:32~12:23 12:32~18:23	93.9	6.1	7.54
Base case	Free-Flow Travel Time	The same time periods as above of the other survey days	88.7	11.3	6.04

To determine the baseline diversion rates, times when the DMS device displayed free-flow travel times are used. During the time periods when diversion messages were posted, the diversion behavior is significant (Masoud, et al., 2011). For instance, in Scenario 1, approximately 10% of I-95 usage decided to switch to I-895 corridor. And 95 effective Bluetooth samples are empirically observed in this case. Similarly, 212 effective samples are extracted in Scenario 2. Thus, in total, 307 testing examples are used in the following calibration process, with real-time travel time information collected by the Bluetooth detectors.

5. ANALYSIS

Naïve Bayesian Classifier

In this paper, the en-route diversion decision is modeled by a naïve Bayesian classifier (see Figure 3). In Figure 3, nodes represent a tuple of stochastic attributes (F_1, F_2, …, F_n) and a classification variable denoted by C. In this paper, we assume that there are only two classes, denoted by: + (i.e. the not-diverting class) or – (i.e. the diverting class). And directed arcs represent conditional dependencies between variables.

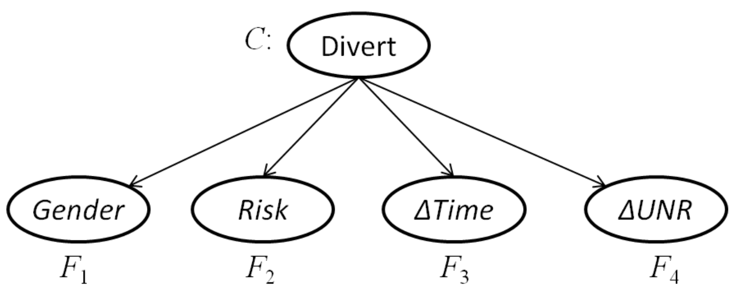

FIGURE 3: the Naïve Bayes Model Structure

Variables F_i that have been used in the model include travel time (*Time*), travel time unreliability (*UNR*), gender (*Gender*), and diverting risk (*Risk*). *UNR* is specified as the 95% confidence interval of the travel time duration. Δ denotes percentage changes from attributes of the normal routes. *Risk* is a dummy variable reflecting the complexity of the diverting route. If the diverting route involves bifurcation and possible huge delay (the situation in *Map B* and *C* shown in Figure 1), even if theoretically the drivers can make the correct en-route decision to avoid the delay penalty with the guidance of the real-time information at the information point *i* (or *i1* and *i2* in *Map C*), drivers are less likely to divert considering the little reaction time in making this decision. This type of diverting routes is considered as a diversion of high risk.

For each training observation **F**, the naïve Bayesian classifier is a function that assigns a class label to it. This method learns the conditional probability of each variable F_i given the class C. According to Bayes' Rule, the probability of the example $\mathbf{F} = (F_1, F_2, \ldots, F_n)$ being class + is:

$$p(+\,|\,\mathbf{F}) = \frac{p(\mathbf{F}\,|\,+)\,p(+)}{p(\mathbf{F})} \tag{1}$$

For a training observation, naïve Bayes classifier assumes conditional independence of every other attributes given the value of the classification variable:

$$p(\mathbf{F}\,|\,+) = p(F_1, F_1, \cdots, F_n\,|\,+) = \prod_{i=1}^{n} p(F_i\,|\,+) \tag{2}$$

Thus, the equation 3 shows the functional form of naïve Bayesian classifier. The empirical observation is classified as + if and only if $f_{nb}(\mathbf{F}) \geq 1$.

$$f_{nb}(\mathbf{F}) = \frac{p(+)}{p(-)} \prod_{i=1}^{n} \frac{p(F_i\,|\,+)}{p(F_i\,|\,-)} \tag{3}$$

The estimated naïve Bayes classifier model using the full training dataset is presented in Table 2. A within-sample ten-fold cross-validation is first conducted for validating the en-route diversion model. The aggregate cross-validation accuracy is 97.7%. This validation technique is typically seen in most practical limited-data situations (Kohavi 1995). When applied to predict diversion behavior, the predictive performance could differ dramatically from the actual observation. For planning and operational application purposes, this model needs to be further calibrated, as more field data becomes readily available.

TABLE 2: Conditional Prior Probability Estimates for the Naïve Bayes Classifier

Class and Class Prior	Variables	Mean	Standard Deviation
Class: + **p (+) = 0.53**	*Gender*	p (*male* | +) = 0.403 p (*female* | +) = 0.597	N/A
	Risk	p (*low* | +) = 0.504 p (*high* | +) = 0.496	N/A
	ΔTime	0.273	0.246
	ΔUNR	0.724	0.223
Class: – **p (–) = 0.47**	*Gender*	p (*male* | –) = 0.468 p (*female* | –) = 0.532	N/A
	Risk	p (*low* | –) = 0.548 p (*high* | –) = 0.452	N/A
	ΔTime	0.058	0.283
	ΔUNR	0.527	0.262

A Bayesian Approach to Calibrating the Naïve Bayesian Classifier

The Naïve Bayesian model assigns to each testing example a score between 0 and 1 that can be interpreted, in principle, as a class membership probability estimate. However, it is well known that these scores are not well-calibrated (Witten et al. 2011).

In Figure 4 we show reliability diagram estimated for the en-route diversion testing dataset where the score space has been discretized into 20 bins. The *x*-axis shows the predicted probability of the naïve Bayesian classifier for the – class (the diverting class). The y-axis shows the empirically observed relative frequency of the – class. If the classifier is well-calibrated, all points should coincide with the diagonal line which indicates that the scores are equal to the empirical probability. The figure demonstrates the effect of overoptimistic probability estimation. Although in general tending to vary monotonically with the empirical probability, the model's prediction is too optimistic, predicting diversion probabilities that are too close to 1. Actually the diversion percentage is much lower than the estimated value. As depicted in Table 2's reported average I-95/I-895 percentages, roughly 1 out of 9 vehicles decide to use the diverting route in Scenario 1 and roughly half vehicles decide to divert in Scenario 2.

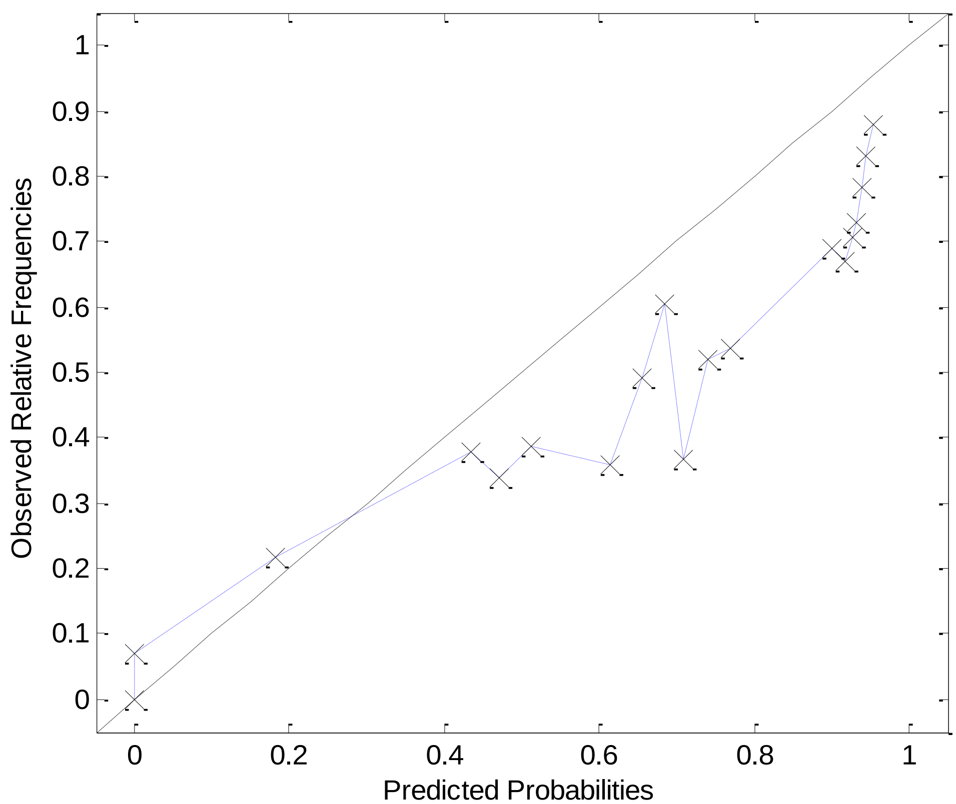

FIGURE 4: Reliability Diagram for the Naïve Bayesian En-Route Diversion Classifier

The Bayesian approach to calibrating the naïve Bayesian classifier is illustrated in Figure 5.

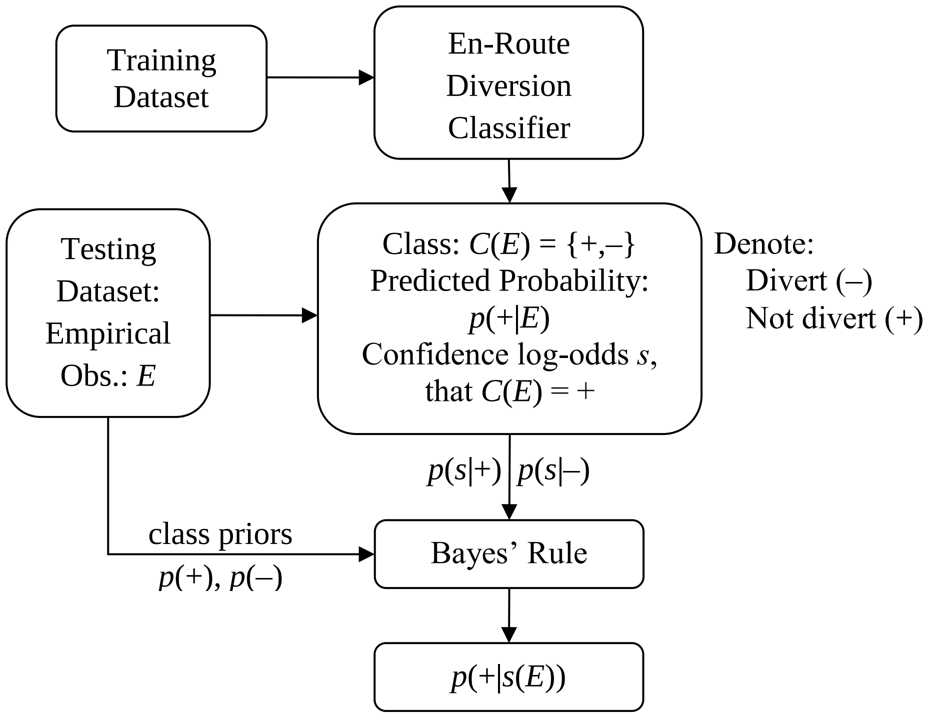

FIGURE 5: A Bayesian Approach to Calibrating the Naïve Bayesian Classifier

The en-route diversion classifier produces a prediction about an empirical data point E in the testing dataset and gives some confidence score $s(E)$ indicating the strength of its decision that the empirical observation belongs to the "not divert" class. The log-odds (equation 5) of the classifier's estimate are usually defined as $s(E)$ for recalibrating a typical data mining classifier (Bennett 2003). This measurement is useful because it scales the outputs from [0, 1] to a space [–∞, +∞] where Gaussian and other distributions are applicable.

$$s(E) = \log \frac{p(+|E)}{p(-|E)} \tag{5}$$

The confidence scores (i.e. the log-odds) and predicted diverting probabilities may not necessarily match the empirically observed probabilities. For recalibrating the classifier, a certain posterior function performing a mapping of the score *s* to the probability *p* (+|*s*(*E*)) is needed in order to obtain a better predicting accuracy. Here the paper breaks down the problem to the two specific classes. An estimator for each of the class-conditional densities (i.e. $p(s|+)$ and $p(s|–)$) is produced for the diversion class and the not-divert class. Then Bayes' Rule and the class priors are used to obtain the estimate for $p(+ \mid s(E))$:

$$p(+|s) = \frac{p(+)\,p(s|+)}{\sum_{C=\{+,-\}} p(C)\cdot p(s|C)} \qquad (6)$$

6. RESULTS

For the calibration function of the class-conditional densities, a Gaussian and a generalized extreme value (GEV) are fit to each of the class-conditional densities using the usual maximum likelihood estimates. The fits of these two functions represent a qualitative comparison between using symmetric distributions and using asymmetric distributions to approximate the class-conditional densities. Figure 6 shows the calibration function fits produced by these methods versus the testing behavior data. Performance measures are offered in the next subsection.

In general, the calibration results agree with the empirical observation. The average value for the naïve Bayes log-odds is approximately -0.5, which is consistent with the low diversion rates perceived from the testing dataset. In other word, the optimistic prediction estimated by the en-route diversion model is well captured and recalibrated by this Bayesian calibration process. For the diversion class (+), the test data curve plotted in Figure 6 skews towards the left side, as the en-route diversion model gives these observations higher probability estimates to divert. And vise versa for the not-divert class (–).

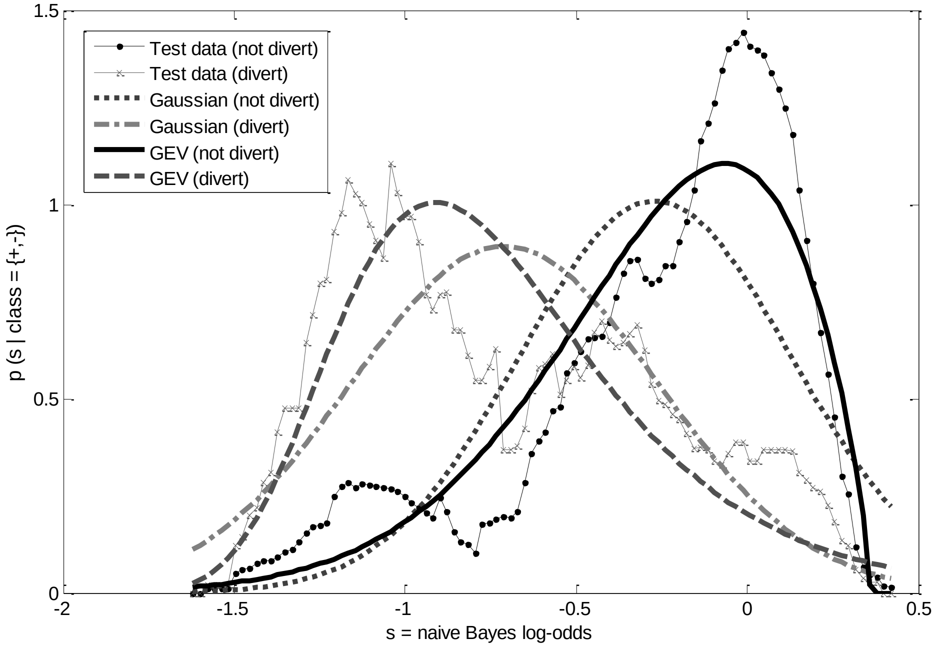

FIGURE 6: Estimated Class Conditional Score Densities versus the Actual Densities of the Testing Dataset

Performance Measures

The calibration function maps the estimated probabilities (i.e. log-odd scores) to the actually observed diversion rates. Now the evaluation of the calibration results is of concern. There are at least two types of performance measures that have been typically used in data mining to assess the quality of probability estimates: i.e. log-loss (Good 1952) and squared error (Brier 1950;DeGroot and Fienberg 1983). While actually meaning an overall improved prediction quality, a better score according to these rules sometimes has been loosely termed improving "calibration" (Bennett 2003).

The actual classification for an empirical observation E (with class $C(E) \in \{ +, - \}$) in the testing dataset is observed. Let δ denote the Kronecker delta function which equals 1 if the two arguments are equal to each other and 0 otherwise. The log-*loss* and the squared error ($Error^2$) are defined as Equation 7 and 8, respectively.

$$\log loss = \delta\left(C\left(E\right),+\right)\log P\left(+\,|\,E\right)+\delta\left(C\left(E\right),-\right)\log P\left(-\,|\,E\right) \tag{7}$$

$$Error^2 = \delta\left(C\left(E\right),+\right)\left(1-P\left(+\,|\,E\right)\right)^2+\delta\left(C\left(E\right),-\right)\left(1-P\left(-\,|\,E\right)\right)^2 \tag{8}$$

This paper reports the average log-loss and mean squared error (*MSE*) for the performance measure of the calibration. The results are given in Table 3. Both calibration functions result in significant improvement for the model's prediction accuracy, as the average log-loss statistic has been improved from -2.99 to -1.26 and -0.69 respectively and the *MSE* has been reduced from 0.19 to 0.13 and 0.09 respectively. And overall, asymmetric distributions (for instance, GEV in this case) tend to be empirically preferable and outperform symmetric distributions in terms of prediction accuracy.

TABLE 3: Results for Calibrating Naïve Bayes Model

	Average Log Loss	**Mean Square Error**
Naïve Bayes	-2.9946	0.1897
Gauss	-1.2625	0.1311
GEV	-0.6861	0.0906

7. CONCLUSIONS

The objective of this paper is to study the en-route diversion responses of drivers under real-time information. To achieve this objective, a Naïve Bayes model is developed for this binary en-route diversion decision (i.e. switch to the diverting route or stay on the normal route). Stated preference data collected from carefully designed driving simulator scenarios is employed in the model estimation. Due to the inherent bias from the simulator data, the prediction accuracy of the naïve Bayes model is shown by this paper to be over-optimistic. Then, this paper provides a Bayesian approach to calibrating the en-route diversion model using real-world en-route diversion data collected from Bluetooth sensors and Dynamic Message Signs.

The first contribution of the paper lies in the originality of the model. As an effective alternative to the typical discrete choice models that assume rationality and random utility maximization, the naïve Bayes classifier estimated by the paper takes a purely probabilistic perspective and predicts the posterior diversion rates based on the class priors. And the Bayesian approach to calibrating the naïve Bayes probability estimates provide a consistent and theoretically sound parametric method to transform the predicted diversion probabilities to the actually observed probabilities. This calibration approach is very flexible and the parameters can be easily estimated on a case-specific basis, which indicates a promising application potential.

This paper also remains a first research effort as an exploration of using Bluetooth-based field data to evaluate and eventually calibrate an en-route diversion behavioral model. It bridges the gap between the real-world en-route diversion situation and the simulated driving experiments and stated scenarios which have been used for modeling for decades.

Given the ease of estimating the parameters of this model as well as the calibration functions, the model is operational, and ready to be integrated with traffic models (e.g.

microscopic traffic simulators, dynamic traffic assignment models) or demand models (e.g. activity-based/micro-simulation models) for various transportation operations and planning applications that require en-route diversion analysis. The case study of I-95/I-895 diversion presented in this paper highlights the potential of applying this model to analyze en-route diversion behavior in congested commuting corridors, help evaluating DMS, ATIS, and other traffic operations strategies, and improve the aforementioned traffic/demand models' sensitivity to real-time traffic information and en-route congestion.

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