2008

A Bayesian-Decision Analysis Framework for the Financial Evaluation of Automatic Incident Detection Devices

Parag C. Pendharkar
Penn State Harrisburg, pxp19@psu.edu

A Bayesian-Decision Analysis Framework for the Financial Evaluation of Automatic Incident Detection Devices

Parag C. Pendharkar
Penn State Harrisburg
pxp19@psu.edu

ABSTRACT

We propose a Bayesian decision analysis framework for the evaluation of automatic incident detection (AID) tools in intelligent transportation systems. The proposed framework can be used by decision makers for financial analysis of AID devices, identify appropriate AID device locations and develop an AID device replacement schedule.

Keywords (Required)

Automatic Incident Detection, Decision Support Systems, Economic Models, Bayesian Reasoning.

INTRODUCTION

In urban freeway operations and traffic management, incidents are defined as probabilistic non-recurring events such as accidents, breakdowns, spilled loads, and other events that disrupt the normal flow of traffic (Srinivasan et al., 2004). In the United States, more than half of congestion on the freeways is caused by incidents and nearly all of the congestion on rural highways is caused by incidents (Liu and Yang, 1998). There are several different approaches to detect incidents on the highway. Among these approaches are conventional automated techniques and operator assisted techniques. Conventional automated incident detection (AID) techniques include loop detectors (most common), video imaging and machine vision techniques. The reliability of video imaging and machine vision techniques varies depending on weather (rain, snow, fog, wind etc.) and artifact conditions (night, dawn/dusk light transitions, camera motion, vibrations etc.) (Michalopoulos et al., 1993), but is generally considered good. Further, all conventional automated techniques use certain computerized algorithms, which are known to impact their reliabilities. Operator assisted methods, while reliable, are labor intensive and expensive because these methods involve humans for detecting, confirming, responding and managing the incidents.

Most of the research on AID devices has focused on developing algorithms for minimizing false alarm rate (FAR) and there are several neural network, fuzzy-logic and image-based processing algorithms available. However, the reliability and timeliness of these algorithms is very elusive. To our knowledge, there are no studies on financial evaluation of AID devices. The high FARs make the financial evaluation of AID devices very important because high FARs translate into wasted time and effort by state government employees. The cost of high FAR for a device may be different depending on where it is located. For example, freeway locations with high likelihood of congestion require more reliable devices because a device with high FAR in such a place will be more costly and can exacerbate congestion. Financial evaluation is also necessary to identify when and which AID device should be replaced? We believe an appropriate AID device evaluation framework will allow decision-makers to manage location, type and replacement schedules of AID devices.

A few researchers in the past have used decision-trees to provide structure for incident frequency breakdowns. Lindley (1986) and Petty et al. (1996) catalog lane vs. shoulder, accident vs. breakdown, and one lane vs. multi-lane in a decision tree. The incident frequency breakdown decision-trees can be combined with the AID device reliability matrix, related costs of device errors and benefits of correct detection to develop a framework that allows for the financial evaluation of an AID device at a particular location.

In this paper, we use Bayesian theory and a decision tree to develop a Bayesian decision analysis framework for financial evaluation of AID tools. In next section, we develop and describe the Bayesian decision analysis framework. In section after next section, we apply the framework evaluate an AID device in a hypothetical example. In last section, we conclude the paper with summary.

THE BAYESIAN DECISION ANALYSIS FRAMEWORK FOR FINANCIAL EVALUATION OF AID TOOLS

Bayes theorem is a useful statistical inference technique that allows a researcher to estimate the likelihood of a property given a set of input data. Assume that one of two mutually exclusive and collectively exhaustive hypotheses, h_1 and h_2, must occur; and x is an observable event, then the posterior probability of hypothesis h_1, given that event x has occurred, can be estimated by the Bayes theorem as follows.

$$P(h_1 \mid x) = \frac{P(x \mid h_1)P(h_1)}{P(x \mid h_1)P(h_1) + P(x \mid h_2)P(h_2)}.$$

The terms $P(h_1|x)$ and $P(h_1)$ in above equations represent *posterior* and *prior* probabilities. The term $P(x|h_1)$ represents *conditional* probability. The other terms related to the second hypothesis can be similarly defined. Prior probability refers to the probability that a hypothesis will be observed when no information about the event x is available. Conditional probability refers to the probability that event occurs with a particular hypothesis. Prior and conditional probabilities are either calculated from historical observations or estimated by an expert. Posterior probabilities are estimated when event information becomes available. Bayes theorem provides a useful relation to estimate posterior probabilities from prior and conditional probabilities.

Bayesian statistics is slightly different from traditional statistics in that there is no need for historical datasets and data sampling. Bayesian statistics can use probability estimates from data, human expert, or combination of data and human expert. Many real-world situations, such as predicting a recession, outcome of a sports event or an election, are suitable for application of Bayesian statistics. In our research, based on Lindley (1986) and Petty et al. (1996), we assume that a decision tree of past incidents is available. We also assume that the costs of not detecting incidents and not providing necessary help (C) and benefits (B) of detecting and providing necessary help for incidents is known. Figure 1 illustrates an example of a decision tree. The variables in the set $\{p_{01}, p_{02}, p_{13}, p_{14}, p_{21}, p_{22}, p_{31}, p_{32}, p_{41}, p_{42}\}$ are known probabilities that are either subjectively estimated or are estimated from past historical data. The variables C_i and B_i $\forall\, i \in \{1,..,6\}$ are known costs and benefits respectively.

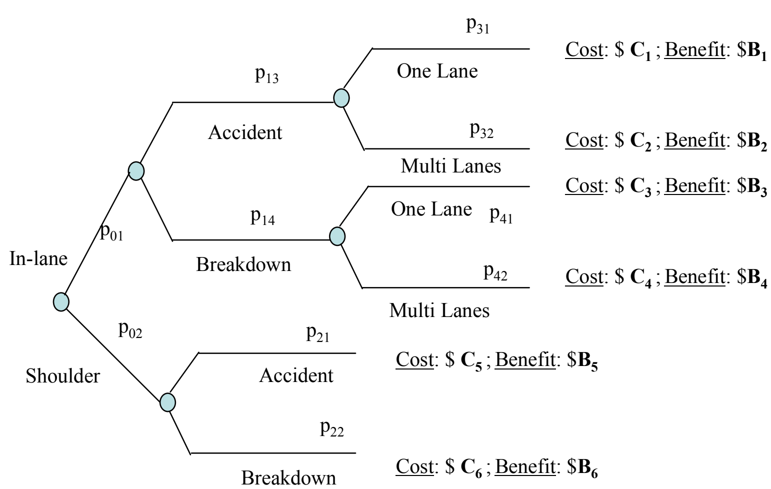

Figure 1: A decision tree of past incidents

Using backward induction on the decision tree shown in Figure 1, the expected cost (*E(C)*) and expected benefit (*E(B)*) of ignoring or sending help for an incident is given as follows.

$$E(C) = \left\{ p_{01}\left(p_{13}\left(p_{31}C_1 + p_{32}C_2 \right) + p_{14}\left(p_{41}C_3 + p_{42}C_4 \right)\right) + p_{02}\left(p_{21}C_5 + p_{22}C_6 \right)\right\}, \text{ and}$$

$$E(B) = \left\{ p_{01}\left(p_{13}\left(p_{31}B_1 + p_{32}B_2 \right) + p_{14}\left(p_{41}B_3 + p_{42}B_4 \right)\right) + p_{02}\left(p_{21}B_5 + p_{22}B_6 \right)\right\}.$$

The transportation administration should setup an AID system in locations where $\left|E\left(B\right)\right|>\left|E\left(C\right)\right|$.

The aforementioned cost benefit analysis assumes correct detection of incidents by AID devices. In real-world situations, AID devices have false alarms, where an incident is detected when in reality there is no incident. We assume that after an AID device is implemented data on historical performance of the AID device is available. If no such data are available, we assume that a specific device is pilot tested to obtain such data. Given historical data, we can obtain following four conditional probabilities:

$P(PI|AI)$, $P(\neg PI|AI)$, $P(PI|\neg AI)$ and $P(\neg PI|\neg AI)$. The probability $P(PI|AI)$ represents a conditional probability that the AID device predicted incident (PI) when actual incident (AI) took place, and the symbol "¬" represents negation. If $P(AI)$ and $P(\neg AI)$ are prior probabilities of actual incidents in a particular locations then prior probabilities of $P(PI)$ and $P(\neg PI)$ for a particular AID device can be obtained by using product rule and marginalization as shown below.

$$P(PI) = P(PI,AI)+P(PI, \neg AI) = P(PI|AI).P(AI)+P(PI|\neg AI).P(\neg AI)$$

$$P(\neg PI) = P(\neg PI,AI)+P(\neg PI, \neg AI) = P(\neg PI|AI).P(AI)+P(\neg PI|\neg AI).P(\neg AI).$$

Given prior probabilities $P(PI)$ and $P(\neg PI)$; conditional probabilities $P(PI|AI)$, $P(\neg PI|AI)$, $P(PI|\neg AI)$ and $P(\neg PI|\neg AI)$; the posterior probabilities $P(AI|PI)$, $P(AI|\neg PI)$, $P(\neg AI|PI)$ and $P(\neg AI|\neg PI)$ can be computed using the Bayes theorem.

We assume that the overhead cost of sending help to a scene of incident is known and fixed at F dollars. When a given AID device with posterior probabilities the posterior probabilities $P(AI|PI)$, $P(AI|\neg PI)$, $P(\neg AI|PI)$ and $P(\neg AI|\neg PI)$, and a known decision tree as shown in Figure 1 is implemented, we have following benefit of sending help when a device predicts incident.

$$Benefit=\left(E\left(B\right)-F\right)P\left(AI\mid PI\right)-F\times P\left(\neg AI\mid PI\right).$$

The cost of not detecting incidents by the AID device is given as follows.

$$Cost=E\left(C\right)P\left(AI\mid\neg PI\right).$$

A reader may note that, for the sake of comparison, the cost of not installing AID will be $E(C)$. This cost will always be less or equal to cost of not detecting incidents by the AID. Thus, the use of an AID device is financially justified when the following rule holds true.

$$\left(E\left(B\right)-F\right)P\left(AI\mid PI\right)>\left|F\times P\left(\neg AI\mid PI\right)+E\left(C\right)\times P\left(AI\mid\neg PI\right)\right|.$$

In next section, we apply this Bayesian heuristic in a hypothetical example.

APPLICATION OF THE BAYESIAN DECISION ANALYSIS FRAMEWORK ON A HYPOTHETICAL EXAMPLE

We use a real-world decision tree from Lindley (1986) and Petty et al. (1996) for our example. There are several papers in literature (Petty, 1996; Fambro et al., 1976; Wohlschlager and Balke, 1992) that describe how to assign cost and benefits of providing assistance to motorists with incidents. Typically, costs are fixed costs of providing assistance by sending tow trucks and other variable costs related to blocking the highway sections, sending police cars and ambulance. The benefits are reduction in congestion and delay. The benefits are measured by multiplying the vehicle delay by time value per vehicle. Figure 2 illustrates the decision tree and associated costs for our example.

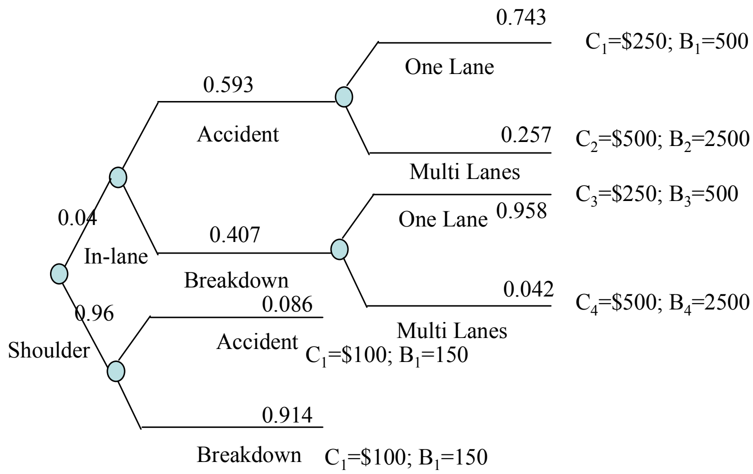

Figure 2: A decision tree and associated costs for the hypothetical example

The expected costs and expected benefits for the decision tree in Figure 2 are given as follows.

$$E(C)=\begin{Bmatrix}0.04\left(0.593\left(0.743\times 250+0.257\times 500\right)+0.407\left(0.958\times 250+0.042\times 500\right)\right)+\\0.96\left(0.086\times 100+0.914\times 100\right)\end{Bmatrix}$$, and

$$E(B)=\begin{Bmatrix}0.04\left(0.593\left(0.743\times 500+0.257\times 2500\right)+0.407\left(0.958\times 500+0.042\times 2500\right)\right)+\\0.96\left(0.086\times 150+0.914\times 150\right)\end{Bmatrix}$$. Thus, $E(C)$ =\$107.69 and $E(B)$ = \$177.56 respectively.

We assume that the prior probability of incidence and prior probability of no incidence is known as follows.

$$P(AI)= 0.2, \text{ and}$$
$$P(\neg AI) = 0.8.$$

We assume that an AID with known conditional probabilities of incident detection, listed in Table 1, is considered in the highway location related to Figure 2. The columns in Table 1 list the probability values of predicted incidence conditioned on the known value of incidence listed in the rows.

Table 1: The known conditional probabilities of AID device

	PI	¬*PI*
AI	$P(PI\|AI)$=0.9	$P(\neg PI\|AI)$=0.1
¬*AI*	$P(PI\|\neg AI)$=0.1	$P(\neg PI\|\neg AI)$=0.9

The prior probabilities of predicted incidence and predicted no incidence for the AID device can be computed as follows.

$$P(PI) = P(PI|AI).P(AI)+P(PI|\neg AI).P(\neg AI)= 0.9\times 0.2+0.1\times 0.8=0.26$$
$$P(\neg PI) = P(\neg PI|AI).P(AI)+P(\neg PI|\neg AI).P(\neg AI)=0.1\times 0.2+0.9\times 0.8=0.74.$$

The posterior probabilities $P(AI|PI)$, $P(AI|\neg PI)$, $P(\neg AI|PI)$ and $P(\neg AI|\neg PI)$ for the AID device can be computed using the Bayes theorem. For example, the posterior probability for $P(AI|PI)$ can be computed as follows.

$$P(AI \mid PI) = \frac{P(AI)P(PI \mid AI)}{P(PI)} = \frac{0.2 \times 0.9}{0.26} = 0.692,$$

$P(AI|\neg PI)$=0.027,

$P(\neg AI|PI)$=0.308, and

$P(\neg AI|\neg PI)$=0.973.

If fixed cost of sending help to a scene of incident F=\$35 then the expected benefit of sending help when a device predicts incident is:

$$Benefit = (177.56 - 35)0.692 - 35 \times 0.308 = \$87.87.$$

The expected cost of not detecting incidents by the AID device is:

$$Cost = E(C)P(AI \mid \neg PI) = 107.69 \times 0.027 = \$2.91.$$

The above expected benefits and costs are per incident. These costs can be multiplied by expected number of incidents on a monthly or annual basis to compute overall periodic benefits or costs.

SUMMARY, SIGNIFICANCE AND FUTURE RESEARCH DIRECTIONS

We have provided a probabilistic Bayesian-Decision Analysis framework to aid financial evaluation of AID devices. Our framework considers the financial impact of an AID device by considering its location (by using decision tree of past incidents) and its performance (by considering historical or pilot test data). By considering the device location and device reliability our framework allows decision makers to combine device context and its performance into the financial analysis. Our framework can allow a decision maker to appropriately compare two AID devices for a particular location by providing exact information on the extent of benefit that a device with low false alarm rate will provide. An important aspect of our framework is that the comparison of two devices is context specific and is not always an absolute comparison. The context information for the device comparison is given by a decision tree for the device location and is reflected in expected costs and benefits of the decision tree.

Our framework is flexible and can be used to develop a replacement schedule of an AID device. For example, the device conditional probabilities (as shown in Table 1) can be continuously updated over the life of the device. As the AID devices get old, the conditional probabilities will reflect that information and posterior probabilities will change resulting in different expected benefits and cost information of a device. Our framework allows for the capture of new traffic incident patterns. The new traffic incident patterns will result in new probabilities for the decision tree (Figure 2) leading to new expected benefits and costs.

There are certain issues that we have not addressed in our research and may be of interest for future researchers. First, the benefit value assignment in our research considered the reduction in delay and congestion, it is possible to consider other qualitative factors such as safety, stress and other factors related to general well being of humans. Second, we consider a fixed cost for sending help. Most real-world incidents will incur variable cost for sending help depending on severity of the incident. For example, a simple car breakdown may only need a tow truck, but a major accident may require a tow truck, an ambulance or even a helicopter to airlift a victim of the accident. Future research is needed to generalize our research and improve its practical significance.

REFERENCES

1. Fambro, D. B., Dudek, C. L., Messer, C. J. (1976) Cost-effectiveness of freeway courtesy patrols in Houston, *Transportation Research Record*, 601, 1-7.
2. Lindley, J. A. (1986) Qualification of urban freeway congestion and analysis of remedial measures, Technical Report RD/87-052, FHWA, Washington, D.C..
3. Liu, W., and Yang, Z. (1998) Control Methods for High Freeway Systems, Beijing, China: Renmin Jiaotong.
4. Michalopoulos, P. G., Jacobson, R. D., Anderson, C. A., and DeBruycker, T. B. (1993) Automatic incident detection through video image processing, *Traffic Engineering and Control*, 34, 2, 66-84.
5. Petty, K., Noeimi, H., Sanwal, K., Rydzewski, D., Skabardonis, A., Varaiya, P., and Al-Deek, H. (1996) The freeway service patrol evaluation project: databases, support programs and accessibility, *Transportation Research*, Part C: Emerging Technologies, 4, 2, 71-85.
6. Srinivasan, D., Jin, X., and Cheu, R. L. (2004) Evaluation of adaptive neural network models for freeway incident detection, *IEEE Transactions on Intelligent Transportation Systems*, 5, 1, 1-11.
7. Wohlschlager, S. D., Balke, K. N., (1992) Incident response and clearance in the state of texas: case studies of four motorist assistance patrols, Technical Report TX-92, 1232-15, FHWA, Texas Transportation Institute, Texas A&M University.