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Real-time prediction of secondary incident occurrences using vehicle probe data

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ABSTRACT

Effective incident management system requires quantifying non-recurring congestion and detecting a secondary incident under the negative influence of a primary incident. Previously suggested thresholds and measurement parameters provide no universal definition of a secondary incident, regardless of discussions on the topic. To solve this dilemma, we propose a Bayesian structure equation model to recognize congestion patterns for road segments using INRIX Data. An adjustment of the boxplot is applied to capture segments at the tail of the queue and at the head of the queue where secondary incidents might occur. The resulting contour plot provides temporal–spatial area under congestion to identify secondary incidents. The likelihood of classified secondary incidents are sequentially predicted from the point of incident response to the road clearance. The prediction performance of the principled Bayesian learning approach to neural networks outperforms the logistic model. The quality of predictions improve as new information (e.g. notification-arrival of response units, speed) becomes available. A pedagogical rule extraction approach will improve the ability to understand secondary incidents by extracting comprehensible rules from the neural networks. The symbolic description represents a series of decisions to assist emergency operators in their decision-making capabilities.

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1. Introduction

Traffic congestion is a major feature of urban areas around the world. Congestion causes almost every motorist to experience significant delays, which results in wasted time and fuel on the road. Every additional vehicle imposes added delay on other drivers, resulting in an economic efficiency loss due to excessive traffic volumes. Unreliable travel time forces motorists to begin traveling much earlier than is normal for short-distance commutes. More than 25% of congestion is caused by nonrecurring events that take away part of the roadway from use. The consequent speed reduction and rubbernecking provoke additional incidents, which are referred to as secondary incidents. The longer an incident scene is in place, the greater the likelihood of a secondary incident (Karlaftis et al., 1999). The total time it takes for an incident to be cleared increases with the occurrence of secondary incidents, and travelers may experience ever-increasing congestion.

To reduce the negative impact of road incidents, it is necessary to efficiently manage incident response units (Lou et al., 2011). However it is difficult to quantify a primary incident's impact on secondary incidents. Previously suggested thresholds and measurement parameters provide no universal definition of a secondary incident, regardless of discussions on the topic. In addition, an estimation result of traffic states significantly depends on performance of data collected from sensors (e.g.

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loop detectors). The speed sensors are prone to various errors caused by malfunctioning and communication failures. Researchers have tried to overcome the limitations of the unsatisfactory quality of sensor data (e.g. Lao et al., 2012). Nevertheless, accurately representing the traffic conditions is a challenge (Washington et al., 2003). Traffic management agencies are faced with dilemma.

We identify negative impacts of primary incidents and predict the occurrence of secondary incidents using INRIX traffic data. As previous models (e.g. Vlahogianni et al., 2012) consider the spatial and temporal influences of a primary incident on road users, our analytical models capture dynamics in traffic congestion and detect potential secondary incidents. We sequentially predict clearance times considering influential factors. At each stage, predicted clearance time is used as one of the factors to predict secondary incident likelihood. A pedagogical rule extraction approach will improve the ability to understand secondary incidents by extracting comprehensible rules from the model.

The remainder of this article is organized as follows. The next section will motivate this work with a literature review. The subsequent sections will provide the reader with models for detecting congestion and secondary incident occurrences, then with performance results of prediction of secondary incidents. Section 5 will introduce pedagogical interpretation of prediction models. The paper will end with a short discussion and conclusions (Section 6).

2. Relevant studies

2.1. Impact of traffic incidents

In recent years, the vehicle probe industry has emerged as a viable means to monitor network-wide traffic flow. The travel time collected from vehicle probe data on the freeway segments generally satisfies the requirements of applications for real-time travel time display (Haghani et al., 2010). This is a new opportunity to use real-time estimations of traffic congestion caused by incidents. One application of vehicle probe data is proposed by Pack (2013) which defined freeway segments as congested using fixed threshold. Contrary to this static bottleneck detection approach, we present variable thresholds for each segment using a clustering and an adjusted boxplot approach. The approach captures the dynamics of traffic evolution by separating congestion from non-congestion present on the road at the time and place of an identified incident.

Estimated delay is caused by the temporal reduction of capacity to the existing traffic conditions due to rubbernecking or physical impedances in the travel lanes. This impact may lead to one or more secondary incidents. It is important to understand the cause and effect of secondary incidents. According to the National Traffic Incident Management Coalition (2007), “stuck-by” secondary incidents are on the rise. Eighteen percent of traffic fatalities occur as a result of secondary collisions (Karlaftis et al., 1999). While each step of incident management system is archived to a database, secondary incidents are not recorded. Traffic Incident Management Performance Measurement (2009) revealed difficulties in determining the precise definition of secondary accidents. We need a robust definition of secondary incidents. Since it has a direct influence on the result, we cannot exaggerate the importance of accurate definition.

The identification of secondary incidents has focused on representing the temporal and spatial thresholds from the impact of primary events, and is classified in two main categories. A static impact area is determined by maximum clearance length and time (e.g. Moore et al., 2004). Compared to the static thresholds, dynamic thresholds conclude that an incident should not be classified as secondary when it occurs far from the primary location of the event without congestion. Different aspects of dynamic models include:

Simulation modeling. It replicates rubbernecking by proportionally increasing the distances at which the vehicles are following one another. Haghani et al. (2006) initiated the study for dynamic thresholds, identified from the shockwave that arises as a consequence of the incident.

Deterministic queuing. It uses the cumulative arrival and departure curve for deterministic estimate of traffic delays and queue lengths (Khattak et al., 2012). Deterministic queuing for real-time application might be less realistic, since it assumes exact arrival rate and capacity reduction (Fu and Rilett, 1997).

Closed-circuit television. Visual devices enabled the observation of the progression of the queue formulated at the upstream. Vlahogianni et al. (2010) defined the spatial-temporal boundary for each secondary crash based on maximum queue length and the duration induced by the crash. It should be noted, however, archived incident data collection is expensive and as a result may have limited queuing information.

Speed contour plot. The speed threshold algorithm is widely adopted in bottleneck identification (Chen et al., 2004). Automatic Tracking of Moving Traffic Jams (ASDA) was used to capture the propagation of wide moving jam (Li and Bertini, 2010). Imprialou et al. (2014) used ASDA model for spatiotemporal evolution of traffic flow and the propagation of the traffic disturbance upstream of the incident. However, relying on loop detector decreases the accuracy of the results. Congestion caused by crashes may not classify pronounced stop-and-go waves described as wide-moving jams (Schönhof and Helbing, 2009). Alternatively, Antoniou et al. (2013) argued ASDA model is more appropriate for use in the context of mesoscopic traffic simulation models. Sun and Chilukuri (2010) marked the end of the varying queue to estimate incident progression curve. Yang (2013) used a set of threshold values to classify a freeway segment as a congested segment. Empirically obtained values may be time consuming and difficult to have a robust measurement to apply for other data. It cannot capture the skewness of the data that may appear at congested freeway sections.

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