SUMMARY: MODELING ENVIRONMENTAL IMPACTS OF TRAFFIC INCIDENTS IN REAL TIME

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ABSTRACT

Timely response to road incidents forms a main part of Traffic Management strategies, as road incidents can have severe environmental and socio-economic impacts. In this work, we propose a framework for real-time incident modeling, based on real-time distress signals from affected vehicles. The framework generates multiple simulations of the possible evolution of the incident and uses them to build a corresponding traffic prediction model. We study the framework empirically through a case study of various incident scenarios in the Hillerød Motorway. The results show that the framework can often yield effective prediction models of the traffic following an incident, thus allowing for more knowledgeable selection of mitigation strategy.

1 Background

As traffic volumes increase constantly around the world, main roads experience more disruptions due to crashes, vehicle breakdowns and adverse weather (Zhang & Batterman, 2013). These disruptions incur not only major travel delays, but also significant socio-economic losses and environmental damages, such as increased pollutant emissions, hazardous material spills and fuel waste (Tupper et al., 2012; Steenbruggen et al., 2012). Incidents and their environmental impacts are thus becoming increasingly pivotal in Traffic Management worldwide (Kong et al., 2013; Mir & Filali, 2016).

Prediction models form a key component of incident management and often rely on commonly available traffic data streams, e.g., as generated by mobile sensors and on-road cameras (Wu et al., 2012). These models thus often require a certain time buffer to both detect and adapt to sudden disruptions, as discussed in (Wu et al., 2012; Ni et al., 2014). Nowadays, however, more and more vehicles are equipped with In-Vehicle Monitoring Systems (EU European Commission, 2015; Viereckl et al., 2016), which communicate real-time distress signals upon vehicle breakdown.

In this work, we leverage these emerging systems to obtain real-time predictive models of the traffic impacts of road incidents, such as congestion, increased emissions, reduced speeds and longer travel times. To this end, we propose a framework that combines two traditionally separate approaches to traffic modeling: data-driven machine learning on one hand, and classic transport engineering tools (such as simulations) on the other hand. Given real-time distress signals, the framework generates multiple simulations, which reflect a likely range of properties of the corresponding incident, and uses their output as data for fitting a specialized machine learning model for the incident.

Further, we experiment the proposed framework on a case study of various incident scenarios in a major, incident-prone motorway in Denmark. For each scenario, the framework yields a traffic prediction model, which we compare against an uninformed model, i.e., one which is unaware of the incident occurrence. The results then show that the informed model often outperforms the uninformed model significantly, thus allowing better incident management to reduce environmental damages. Our experiments also demonstrate that each incident is unique in its impact and manner of evolution over time.

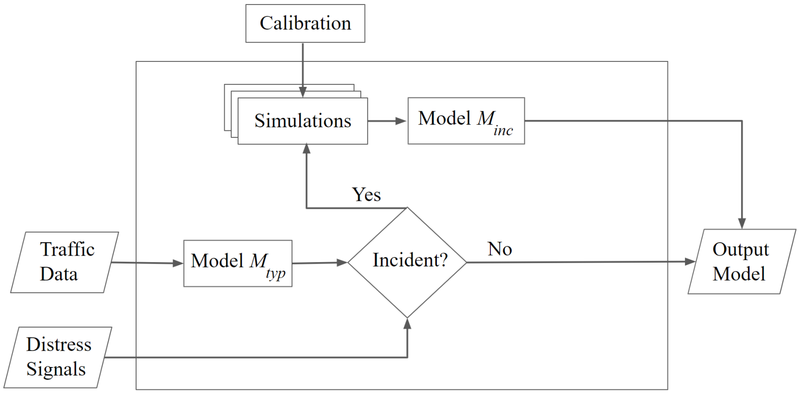

Figure 1: Structure of the proposed framework.

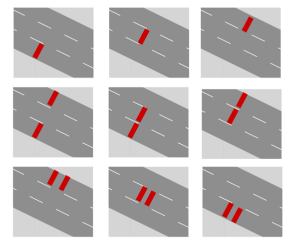

Figure 2: Lane blocks in the case study.

2 Methodology

Figure 1 summarizes the main components of our framework, as follows. The input consists of both a consistent feed of traffic data and distress signals upon incident occurrence. Under typical, incident-free conditions, the framework periodically fits and outputs traffic prediction model M_{typ}, whereas upon receiving incident information in distress signals, it trains and outputs a corresponding model M_{inc}. The framework is agnostic to the choice of models, e.g., M_{typ} and M_{inc} can be parametric or non-parametric, interpretable or black-box, standalone or ensemble, etc.; for completeness, we also provide useful guidelines for model selection.

The framework obtains M_{inc} by running incident simulations to cover a range of unobserved variables – namely, missing from distress signal information – which determine the severity of incident impact. The framework also employs an external component to construct and calibrate the simulated environment, as we focus on the theoretical study of challenges and benefits in extracting value from real-time signals with limited incident information. Indeed, our results later show that even partial incident information can still be useful for noticeably improving traffic prediction quality.

We evaluate the framework on a case study of various incident scenarios in the Hillerød Motorway, for which we use PTV VISSIM as the underlying simulation engine. In all scenarios, either 1 or 2 vehicles suddenly break down at some location on the Motorway (Start, Middle, End), thus blocking one or more of three lanes (Top, Center, Bottom), as illustrated in Figure 2. The scenarios further differ in a couple of unobserved variables: level of road usage (Low, Medium, High) and location precision in distress signals. In total then, the case study has 81 incident scenarios.

The data in these experiments consists of flows, average speed and travel times, as measured in the Motorway in June 2016 by the Danish Road Directorate. We use this data to both calibrate the simulated environment of the Motorway and fit and test three types of models: Linear Regression, Deep Neural Networks, and Gradient Boosting. For each model type and incident scenario, the framework thus yields model M_{inc}; separately, we also generate incident-free simulations, and use them to fit model M_{typ}.

Vehicle emissions are known to depend functionally on average vehicle speed (Shridhar Bokare & Kumar Maurya, 2013; Hao et al., 2017). Consequently, for all M_{inc} and M_{typ}, the modeled target variable is the 1 min average speed in the Motorway. We note, however, that the same methodology can be used to model other emission factors, e.g., traffic flow and standstill duration; emissions can further be simulated and modeled directly, e.g., using the MOVES component of VISSIM.

3 Results

Models aside, we first analyze the typical behavior of 1 min average speed for each of the 81 incident scenarios. We find that on one hand, the patterns of speed change can be partitioned into a few discernible classes, while on the other hand, each incident differs in the way it particularly evolves over time.

Next, we measure the predictive performance of each model in terms of Mean Rooted Squared Error (RMSE) for each incident scenario. All M_{inc} models perform better when blocked lanes are known than otherwise, and all M_{typ} models

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			High		Medium		Low	
			Precise	Impreise	Precise	Impreise	Precise	Impreise
Start	Bottom	Bottom	0.07	0.13	0.05	0.30	0.27	0.50
		None	0.13	0.16	0.38	0.43	0.25	0.29
	Center	Bottom	0.13	0.18	0.54	0.26	0.49	0.59
		Center	-0.21	0.04	-0.03	0.32	-1.11	-0.21
		None	0.16	0.18	0.06	0.05	0.35	0.26
	Top	Bottom	0.11	0.10	0.46	0.48	0.47	0.70
		Center	0.20	0.26	0.39	0.55	0.44	0.72
		Top	-0.52	0.22	-0.35	0.07	-0.37	0.27
		None	0.15	0.04	-0.16	0.07	0.34	0.29
Middle	Bottom	Bottom	0.23	0.41	-0.12	0.31	-1.24	0.11
		None	0.37	0.32	0.40	0.37	0.37	0.33
	Center	Bottom	0.57	0.59	0.53	0.83	0.63	0.73
		Center	0.03	0.38	0.15	0.44	-2.19	-0.11
		None	0.28	0.27	0.31	0.29	-1.02	-1.03
	Top	Bottom	0.50	0.68	0.51	0.81	0.55	0.82
		Center	0.51	0.78	0.52	0.80	0.60	0.76
		Top	0.52	0.44	0.38	0.44	-2.58	-0.39
		None	0.36	0.31	0.26	0.27	-0.13	-0.34
End	Bottom	Bottom	0.24	0.56	0.08	0.24	-0.59	0.36
		None	0.58	0.57	0.44	0.43	-0.30	-0.29
	Center	Bottom	0.60	0.75	0.54	0.71	0.63	0.73
		Center	0.24	0.48	-0.02	0.46	-1.22	0.22
		None	0.51	0.49	0.37	0.35	0.17	0.18
	Top	Bottom	0.63	0.78	0.59	0.85	0.64	0.78
		Center	0.70	0.76	0.60	0.79	0.63	0.77
		Top	0.12	0.46	0.13	0.39	-0.36	0.45
		None	0.50	0.54	0.31	0.31	0.30	0.24

Figure 3: Improvement in predictive performance of Linear Regression for each incident scenario in the case study. Rows pertain to location on incident link, 1st blocked lane and 2nd blocked lane (if any). Columns pertain to road usage level and location precision in distress signals.

deteriorate under incident scenarios. For M_{inc}, Linear Regression mostly outperforms both Deep Nerual Networks and Gradient Boosting, possibly because of suboptimal hyper-parameter tuning or overfitting due to model complexity.

Finally, we measure the improvement in predictive performance admitted by the framework. For this, we compare Linear Regression M_{typ} to M_{inc}, as

$$\frac{\text{RMSE}\left(M_{typ}\right) - \text{RMSE}\left(M_{inc}\right)}{\text{RMSE}\left(M_{typ}\right)},$$

such that higher values correspond to better performance of M_{inc}. The results appear in Figure 3, which shows that for the majority of scenarios, M_{inc} significantly outperforms M_{typ} (blue). There are also a few incident scenarios where M_{typ} outperforms M_{inc} (red), mostly for Low road usage with Precise location information, and we explore possible reasons for this discrepancy.

4 Conclusion

We have devised a framework for real-time traffic modeling of road incidents, based on distress signals from affected vehicles. A case study of vehicle breakdowns in the Hillerød Motorway shows that the framework is capable of timely and effective traffic modeling, given partial information about an incident. Our framework thus promotes an opportunity for timely response to non-recurrent incidents, to mitigate their environmental and socio-economic impacts.

Among the topics of Trafikdage 2020, we feel that this work fits best into Trafikmodeller og Deres Anvendelse (Traffic Models and Their Use). Alternatively, this work also fits into Intelligente Transportløsninger (Intelligent Transport Solutions) and Trafiksikkerhed (Traffic Safety).

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