Traffic incident duration prediction based on deep survival analysis

先介绍背景，然后综述分析，然后介绍基本方法，介绍数据，介绍结果。

背景

Introduction

With the continual increasing of volume to capacity of the road network in cities and the highways between cities, sometimes a small traffic incident will cause serious congestion on the road, let alone these more serious long-time duration traffic incidents. In recent years, various traffic incidents have become one of the main cause of traffic congestion in the cities and the highway networks. In order to reduce the influence of a larger number of traffic incidents, various traffic incident management systems (TIMS) have been established in the traffic operation center in many cities. One most important basic of TIMS is to predict the duration of traffic incident more accurately to support the deployment of appropriate traffic management strategies.

Many kinds of methods have been applied in traffic incident duration prediction([Li et al., 2018](#_ENREF_21)), in which survival analysis model is a widely used methods used in past two decades. Normally the traditional survival analysis assumed that the risk is a linear combination of their covariates which sometime is too simplistic in real world datasets. Recently the neural networks had been used to model the nonlinear proportional hazards of real survival datasets([Ranganath et al., 2016](#_ENREF_29)). This paper mainly aims to investigate the potential of deep learning to survival analysis in traffic incident duration time prediction.

The rest of the manuscript is organized as follows: In section 2, we proposed the implementation of deep learning technique in survival analysis in traffic incident duration time. In section 3, we described the used data and the results shown in section 4. Section 5 gives the conclusion of this manuscript and the future research topic.

（背景）

（谈谈持续模型的应用）

In order to improve the efficiency of traffic incident management in a city or within a highway section, for various traffic incidents, traffic operators must understand the main factors that influence the duration of different traffic incidents and predict the traffic incident duration accurately. In the past two decades, this research field has been examined with many various techniques. Some typical statistics techniques are the following: linear/non-parametric regression ([Garib et al., 1997](#_ENREF_9); [Khattak et al., 2012](#_ENREF_15); [Khattak et al., 2016](#_ENREF_16)), Bayesian classifier([Ozbay and Noyan, 2006](#_ENREF_27)), hazard-based duration model (HBDM) ([Qi and Teng, 2008](#_ENREF_28); [Li et al., 2015](#_ENREF_19)), structure equation model (SEM)([Lee and Wei, 2010](#_ENREF_18)), and discrete choice model([Lin et al., 2004](#_ENREF_23)). However, studies have demonstrated mixed results. The mean absolute percent error (MAPE) is the most frequently applied measurement to investigate the accuracy of the traffic incident predictions and most prediction results is only reasonable as MAPE shown. One reason is that the statistical models tend to capture the central tendency in the data rather than the outliers to a certain extent. For example, [Valenti et al. (2010)](#_ENREF_32) compared five different models(Multiple Linear Regression (MLN), Prediction/Decision tree (DT), Artificial Neural Network (ANN), Support/Relevance Vector Machine (RVM) and K-Nearest-Neighbour (kNN)) for traffic incident duration time prediction and found that only the ANN-based model can predict an incident longer than 90 min.

（上段说统计学方法有应用，但效果不佳）

Recently, based on data-driven empirical algorithms and supported by unprecedented data availability, different data mining (DM)-machine learning (ML) approaches have been employed to estimate and predict the traffic incident duration time; some typical approaches are the following: decision trees (DT) and classification trees model (CTM) ([Zhan et al., 2011](#_ENREF_38); [Lin et al., 2016](#_ENREF_22)), artificial neural networks (ANN)([Wei and Lee, 2007](#_ENREF_35); [Lee and Wei, 2010](#_ENREF_18); [Vlahogianni and Karlaftis, 2013](#_ENREF_33)), and genetic algorithm (GA) ([Lee and Wei, 2010](#_ENREF_18)). The results, however, normally are not good enough because some limitation, such as the availability of data resources, the nature of randomness of traffic incident duration distribution and the different characteristic of the peoples involved in a traffic incident. For example, one study carried by [Zhan, Gan and Hadi (2011)](#_ENREF_38) shown that the developed model based on M5P tree algorithm can generally achieve better prediction results than the traditional regression and decision tree models, nevertheless, the MAPE is 42.7%, which is just a reasonable results. Another study conducted by [Lee and Wei (2010)](#_ENREF_18) shown that, for the proposed feature selection method, the MAPE for predicting incident duration at each time point is mostly under 29%, which indicates that these models have a reasonable forecasting ability.

（然后说说数据挖掘的方法，似乎效果也一般）

Hazard-based duration model is a typical technique to study the duration of an event, and has been extensively applied in a number of fields in civil engineering([Duchesne et al., 2013](#_ENREF_7)) and transportation system. one typical application fields in transportation is traffic incident duration estimation and predication. Two different approaches can be used to incorporate the effect of external covariates on the hazard function: the proportional hazard (PH) and accelerated failure time (AFT) models ([Washington et al., 2011](#_ENREF_34)). When a correct distribution can be ascertained, the AFT model is preferable. However, relevant literatures have revealed that a given AFT model may not always be appropriate. For example, the incident duration time may have Weibull([Nam and Mannering, 2000](#_ENREF_26); [Hojati et al., 2014](#_ENREF_13)), log-normal([Giuliano, 1989](#_ENREF_12); [Chung and Yoon, 2012](#_ENREF_5)), log-logistic([Chung et al., 2010](#_ENREF_4); [Chimba et al., 2014](#_ENREF_3)), or generalized F distributions([Ghosh et al., 2012](#_ENREF_10); [Ghosh et al., 2014](#_ENREF_11)). Although various methods can be employed to assess the goodness of fit of an AFT model, verifying the distributional assumptions adopted in the model is difficult, and the inference can be very sensitive to used distributions. The PH model is considered “robust,” which means that even though the baseline hazard is not specified, reasonably good estimation results of regression coefficients, hazard ratios of interest, and adjusted survival curves can be obtained for a wide variety of data situations ([Kleinbaum and Klein, 2005](#_ENREF_17)). Thus, the results of the PH model closely resemble those of the AFT model with the correct distribution. As an effective technique to study the duration of an event, HBDM models have some advantages in estimate and predict traffic incident duration time. HBDM remains a significant, potential method for future work, but it needs to consider heterogeneity, variation in time, and randomness in modelling.

In the past few years, there are some efforts to improve the performance of HBDM models in traffic incident duration prediction models. One approach is to establish time sequential procedure with HBDM ([Qi and Teng, 2008](#_ENREF_28); [Li, Pereira and Ben-Akiva, 2015](#_ENREF_19)) to make full use of the available information with time goes on, which shown that the accuracy of traffic incident duration prediction increases as more information is incorporated into the developed models. Another approach is to try to capture the distribution more accurately, for example, due to the limitation of single distribution function, [Zou et al. (2016)](#_ENREF_40) applied finite mixture model to describe different shapes of the hazard function and this study found that the mixture modelling approach is a useful method to analyze heterogeneous incident duration data and predict incident duration.

As a powerful data-mining methodology, various NN models have been used widely in civil engineering ([Sinha and Pandey, 2002](#_ENREF_31); [Butcher et al., 2014](#_ENREF_1); [Dai et al., 2014](#_ENREF_6)). On the other hand, transportation engineering is also an research filed in which various NN models have been applied for many years ([Zhang and Ge, 2013](#_ENREF_39)) ([Celikoglu, 2013](#_ENREF_2); [Zeng and Zhang, 2013](#_ENREF_37)). NN models have a great advantage in dealing with non-linear problems. Most of various HBDM models applied to predict the traffic incident duration time have an assumption with the linear risk functions, which maybe a little simplistic as the traffic incident duration time has some randomness and nonlinearity. In the past decades, some researchers([Faraggi and Simon, 1995](#_ENREF_8)) have attempted to model the nonlinear proportional hazards of real survival datasets using neural networks (NN), which can learn nonlinear functions. However, limited by the development NN in past, some studies([Faraggi and Simon, 1995](#_ENREF_8); [Xiang et al., 2000](#_ENREF_36); [Sargent, 2001](#_ENREF_30)) failed to demonstrate improvements beyond linear Cox proportional hazards model. for example, a comparison study conducted by [Mokarram et al. (2017)](#_ENREF_25) shown that when the survival time distribution is known, the survival parametric model is better, while when the survival time distribution is doubt and nonlinear hazard models with high complexity are used, then the ANNs seems be more suitable.

（谈谈普通NN与风险模型的组合效果并不优）

Many previous studies ([Nam and Mannering, 2000](#_ENREF_26); [Li et al., 2015](#_ENREF_20)) shown that the factors influencing traffic duration time are complicated, the survival time distribution is doubt and the relationship between factors and duration time is non-linear. One reason for some NNs network not outperform the linear CPH maybe the fact that neural network practice at the time was not mature. Recently, the development of deep learning technique makes it possible to improve the performance of NN models. [Katzman et al. (2016)](#_ENREF_14) developed a deep Cox Proportional Hazards Network (DeepSurv) based on the architecture proposed by Faraggi and Simon to model survival data, and the results shown that the DeepSurv model actually has better prediction performance on survival data with linear and nonlinear risk functions. A study carried by [Ranganath, Perotte, Elhadad and Blei (2016)](#_ENREF_29) shown that the proposed deep survival analysis, a hierarchical generative approach to survival analysis, is superior in stratifying patients according to their risk. ([Luck et al., 2017](#_ENREF_24)) proposed a deep learning method to predict survival times, which is shown outperformed other common survival analysis methods in terms of survival time prediction quality and concordance index.

（谈谈有深度学习，然后论文结构）

Model development

Data description

Results

Conclusion

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