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# Rule extraction from an optimized neural network for traffic crash frequency modeling

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ABSTRACT

This study develops a neural network (NN) model to explore the nonlinear relationship between crash frequency and risk factors. To eliminate the possibility of over-fitting and to deal with the black-box characteristic, a network structure optimization algorithm and a rule extraction method are proposed. A case study compares the performance of the trained and modified NN models with that of the traditional negative binomial (NB) model for analyzing crash frequency on road segments in Hong Kong. The results indicate that the optimized NNs have somewhat better fitting and predictive performance than the NB models. Moreover, the smaller training/testing errors in the optimized NNs with pruned input and hidden nodes demonstrate the ability of the structure optimization algorithm to identify the insignificant factors and to improve the model generalization capacity. Furthermore, the rule-set extracted from the optimized NN model can reveal the effect of each explanatory variable on the crash frequency under different conditions, and implies the existence of nonlinear relationship between factors and crash frequency. With the structure optimization algorithm and rule extraction method, the modified NN model has great potential for modeling crash frequency, and may be considered as a good alternative for road safety analysis.

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## 1. Introduction

In recent decades, numerous models of crash frequency have been proposed to model the relationship between crash frequency at road segments or intersections and risk factors related to traffic and geometrical characteristics of the sites. Most studies of this sort have employed statistical count modeling techniques, since these models provide explicit forms for the random, discrete and non-negative nature of counting crash data and the effects of major contributing factors on crash occurrence. In addition to statistical models, some artificial intelligence (AI) models have been proposed (Chang, 2005; Li et al., 2008). As a common class of AI models, neural network (NN) models have been successfully used in many fields of transportation research, including highway safety analysis (Karlaftis and Vlahogianni, 2011).

In modeling crash frequency, NNs are able to approximate the potential nonlinear and complicated relationship between crash frequency and risk factors. Several studies have demonstrated the better model fitting and predictive performance of NNs over traditional negative binomial (NB) models, in which nonlinear safety effects of risk factors have been identified (Chang, 2005; Xie et al., 2007). The recently-developed random parameters (Anastasopoulos and Mannering, 2009) and Markov switching (Malyshkina et al., 2009) count models indicate that loosening the constraint of fixed parameters could significantly improve their performance on modeling crash frequency, which also partially reflects the existence of nonlinear relationship in crash modeling.

However, NNs have two primary drawbacks that limit their application to traffic safety research, including the so-called “black-box” characteristic and the possible over-fitting problem (Xie et al., 2007). The black-box characteristic has limited NNs’ ability to explicitly illustrate the effects of explanatory variables on crash frequency. Even for studies using sensitivity analysis, the impacts on safety of each risk factor cannot be systematically or globally interpreted either. To overcome this problem, a more general approach

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is to extract the knowledge from the NNs. Using regression analysis, Setiono and Thong (2004) proposed a rule extraction method that generated a group of piecewise linear functions to approximate NNs. This method may be adopted in road safety analysis to clarify the relationship between network output(s) and input risk factors.

The possible over-fitting problem may be caused by the weak generalization ability of models, which was also observed in generalized linear models (Marzban and Witt, 2001). Sample size and model architecture are two factors that may have a profound effect on NNs' generalization performance (Haykin, 2009). Although Bayesian neural network (BNN) has been proposed to reduce the over-fitting phenomenon, it is not suitable for rule extraction (Xie et al., 2007). For a given sample size, optimizing the structure of NN models, that is, adjusting the number of units or neurons in each layer and the connections between different neurons, is a useful method for improving the model's generalization ability. Moreover, this method can identify and prune factors that have no significant effects on the crash frequency. In previous studies (Chang, 2005; Xie et al., 2007), only the number of hidden layer units was locally optimized by using cross-validation, which can neither guarantee the models' generalization performance nor verify the importance of the input variables. Recently, many advanced methods for NN model structure optimization have been proposed to achieve an optimized network that are able to not only represent more generalized relationship between crash frequency and risk factors, but also create a simpler set of extracted rules (Setiono and Thong, 2004).

Therefore, it would be interesting to research on the possibility of employing the emerging NN techniques in better modeling crash frequency. This study aims to develop a generalized NN model for crash frequency analysis, in which only the significant risk factors are retained with estimation of their effects on crash frequency.

## 2. Literature review

### 2.1. Statistical models of crash frequency

Statistical models have always been the most popular approach for modeling crash frequency. To handle the possible over-dispersion, multilevel heterogeneities, and spatiotemporal correlation among observations, models ranging from the negative binomial (NB) (Miaou, 1994), Poisson-lognormal (Miaou et al., 2005), and zero-inflation models (Shankar et al., 1997; Huang and Chin, 2010) to the Conway-Maxwell-Poisson (Lord et al., 2008), finite mixture/latent class (Park and Lord, 2009; Park et al., 2010), Markov switching (Malyshkina et al., 2009), random effects or random parameters (Shankar et al., 1998; Anastasopoulos and Mannering, 2009), multilevel (Huang and Abdel-Aty, 2010; Lee et al., 2015; Wang and Huang, 2016), and Bayesian spatial models (Dong et al., 2014, 2015, 2016; Huang et al., 2016; Xu et al., 2014; Xu and Huang, 2015), have been widely investigated. Most of these models are based on a generalized linear function framework and certain assumed distributions of crash data. If these assumptions are violated, the inferences about the effects of the related factors may become biased (Li et al., 2008). Lord and Mannering (2010) and Mannering and Bhat (2014) have presented more detailed descriptions and assessments of these models.

### 2.2. NN models of crash frequency

Unlike the statistical models, NN models are not limited by data assumptions and have been used to model the potential nonlinear relationship between crash frequency and related factors. Probably because of the aforementioned two limitations, only a few studies have focused on predicting crash frequency using NN models. Chang (2005) compared the use of NB and NN models for crash frequency analysis, and found that the NN model has better predictive performance. Xie et al. (2007) developed a BNN model for analyzing crash frequency and compared the BNN model, NB model, and NN model trained with a back-propagation (BP) algorithm (BPNN). The results showed that both the BNN and BPNN had higher prediction accuracies than the NB model.

### 2.3. NN structure optimization

Basically, the structure of NN models can be optimized by either constructing or pruning the network. In the constructing method, an NN starts with a small number of hidden layer neurons, and then hidden units are incrementally added during training until the training error cannot be reduced. The most common constructing algorithms include the growing cell structure (GCS) (Fritzke, 1994), constructive back-propagation (CBP) (Lehtokangas, 1999), and adaptively constructing methods (Ma and Khorasani, 2003). Although these constructing algorithms are computationally efficient, they cannot ensure that all of the added units in the hidden layers are properly trained.

For the pruning algorithms, an NN model is firstly created with sufficient hidden layer units. During or after network training, irrelative connections or redundant neurons in the network are removed. Popular pruning algorithms include the optimal brain surgeon (OBS) (Haykin, 2009), subset-based training and pruning (SBTP) (Xu and Ho, 2006), and independent component analysis (ICA) (Nielsen and Hansen, 2008). In contrast to the methods that delete one connection at a time, the NN pruning of the function approximation (N2PFA) algorithm proposed by Setiono and Leow (2000) removes one hidden/input node each time, which could significantly shorten the computational time.

### 2.4. Rule extraction of NN

A large number of rule extraction methods have been developed to make up the black-box characteristic of NNs (Elalfi et al., 2004; Hruschka and Ebecken, 2006). However, only a couple of methods have been devised to extract rules from NNs used for regression problems. Setiono et al. (2002) proposed extracting piecewise linear function rules from NNs. In that study, the hidden unit transfer function was approximated by either a three-piece or a five-piece linear function, which minimized the approximation errors. To generate a simpler and more accurate rule-set, Setiono and Thong (2004) developed a new three-piece linear function form that had comparable approximation performance with the NN model. This method can be modified to further improve its performance and be adopted in road safety analysis to reveal the relationship between safety performance and input factors.

## 3. Methodology

The NB model is one of the most widely used statistical models in crash frequency analysis. As in previous research, it is used as a benchmark in this study, and various techniques are used to compare its predictive performance with that of the NN models. In this section, the model architectures of the NB and NN models are specified. Then, the training, structure optimization, and rule extraction algorithms for the NN model are presented.

### 3.1. Model specification

#### 3.1.1. NB model

The NB model, also known as the Poisson-gamma model, is a modification of the basic Poisson model that can address the com-

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