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Comparison of Multivariate Poisson lognormal spatial and temporal crash models to identify hot spots of intersections based on crash types

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ABSTRACT

Most of the studies are focused on the general crashes or total crash counts with considerably less research dedicated to different crash types. This study employs the Systemic approach for detection of hotspots and comprehensively cross-validates five multivariate models of crash type-based HSID methods which incorporate spatial and temporal random effects. It is anticipated that comparison of the crash estimation results of the five models would identify the impact of varied random effects on the HSID. The data over a ten year time period (2003–2012) were selected for analysis of a total 137 intersections in the City of Corona, California. The crash types collected in this study include: Rear-end, Head-on, Side-swipe, Broad-side, Hit object, and Others. Statistically significant correlations among crash outcomes for the heterogeneity error term were observed which clearly demonstrated their multivariate nature. Additionally, the spatial random effects revealed the correlations among neighboring intersections across crash types. Five cross-validation criteria which contains, Residual Sum of Squares, Kappa, Mean Absolute Deviation, Method Consistency Test, and Total Rank Difference, were applied to assess the performance of the five HSID methods at crash estimation. In terms of accumulated results which combined all crash types, the model with spatial random effects consistently outperformed the other competing models with a significant margin. However, the inclusion of spatial random effect in temporal models fell short of attaining the expected results. The overall observation from the model fitness and validation results failed to highlight any correlation among better model fitness and superior crash estimation.

1. Introduction and background

During the year of 2014, 32,675 fatalities occurred on the US roads and the number of injuries and trauma sufferers is far greater at 2,338,000 annual injuries. In addition, road accidents were the leading cause of death among ages 16 through 24 in 2014 (NHTSA, 2016). The fatalities reflect a significant proportion of healthy lives which could have been saved by the application of appropriate safety countermeasure treatments. The traffic management processes which address safety issues include network screening, problem diagnosis, countermeasure identification, and project prioritization. Among these processes, detection of high risk sites (also called hotspots, black spots, sites with promise, etc.) is of paramount importance for the improvement of driving environment from the safety perspective. The consequences of inaccurate identification would result in two scenarios. First, the screening process may detect truly safe sites as unsafe. Second, truly unsafe sites are not detected, and thus the opportunity to treat the real hotspots is missed.

In general, the network screening follows into two categories: the Systemic Approach and Spot Location Approach (Preston et al., 2013). Comparatively speaking, the latter one is more traditional and relies heavily on the crash history to screen out the most unsafe locations which need remediation. Under Spot Location approach, upon completion of screening, the next step of problem diagnosis is conducted on the identified locations where site issues are usually revealed through the overrepresentation of certain crash outcomes such as rear-end, head-on, and others. Further, safety countermeasures are implemented to enhance the roadway safety situation. The effectiveness of such countermeasures is normally assessed on

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the basis of their benefit of crash reduction and the deployment cost. The Spot Location approach has been very popular among researchers and widely used in practice. The hot spot identification (HSID) methods of this type range from classical crash count (Deacon et al., 1975) and crash rate (Norden et al., 1956) methods to more sophisticated ones including Empirical Bayes (Hauer et al., 2002; Cheng and Washington, 2005; Persaud et al., 2010; Wu et al., 2014) and Full Bayesian approaches (Davis and Yang, 2001; Washington and Oh, 2006; Huang et al., 2009; Lan et al., 2009; Persaud et al., 2010), which can obliterate the Regression to the Mean (RTM) bias (Hauer, 1986; Hauer, 1996; Persaud, 1988; Hauer, 1997; Carriquiry and Pawlovich, 2004) associated with observed crash count data. Some researchers flag out the hazardous locations based on potential safety improvement or "excess" crashes (Jiang et al., 2014), while others conduct HSID through the Level of Service of Safety (Kononov and Bryan, 2003, 2004). Finally, a study by Miranda-Moreno et al. (2009) recommends incorporating crash severity and occupancy into site ranking. One condition of the success of the above mentioned Spot Location HSID methods is the availability of crash history for sites under investigation. This may become an issue in some situations. For example, there is non-availability of robust crash data for lots of rural areas, especially for the occurrence of severe crashes with typically low density (Preston et al., 2013). In such instances, the traditional Spot Location approach sometimes tends to underperform in HSID and the procedure may result in low safety benefits (Local Road Safety, 2015). This issue can be addressed by the Systemic approach, which is relatively new and tends to bridge the gap between hotspot detection and countermeasures implementation (Sawyer et al., 2011). Rather than filter out the sites based on crash history, this method is somewhat proactive and targets the sites lacking safety measures to prevent a specific type of crash. It mainly involves the implementation of remedial safety countermeasures, which are previously proven efficient for certain crash types, such as run-off road crashes, at multiple crash locations, corridors, or geographic areas (Wang et al., 2014). In many cases, this method is more cost efficient than the Spot Location one due to the large scale impact. A major characteristic of the Systemic Approach is the crash type-oriented HSID, and a clear understanding of the interaction between crash count of various types and their causal factors is important for the successful implementation of such approach.

Most of the studies are focused on the general crashes or total crash counts while considerably less research has been dedicated to different crash types. Qin et al. (2005) employed Markov Chain Monte Carlo methods to develop Poisson regression models and found a nonlinear relation between crashes and daily volume, and variation in the relationship for different crash types: single-vehicle, multivehicle same direction, multivehicle opposite direction, and multivehicle intersecting. Kim et al. (2006) used univariate Poisson and Negative Binomial models for crash counts of different types at 160 rural intersections. Data suggests that different pre-crash conditions were linked with crash types and models based on prediction of total crash frequency may fail to identify pertinent countermeasures. Subsequently, Kim et al. (2007) used Binomial multilevel modeling techniques to validate the presence of hierarchical structure in crash data which points towards the causal mechanisms in vehicular crashes (Angle, head-on, rear-end, and sideswipe) due to their relationship with roadway, environmental, and traffic factors. Some studies employed the multivariate approach for simultaneously modeling different crash outcomes (Aguero-Valverde and Jovanis 2009; Zhan et al., 2015). The effects of weather on crash types were explored by El-Basyouny et al. (2014) using Bayesian multivariate Poisson lognormal models for the prediction of seven crash types (Follow-Too-Close, Failure-To-Observe-Traffic Signal, Stop-Sign-Violation, Left-Turn-Across-path, Improper-Lane-Change, Struck-Parked-Vehicle, and Ran-Off-Road). This study established the strong significance of temperature, snowfall, and day of week on occurrence of different types of crashes. More recently, Jonathan et al. (2016) applied Bayesian multivariate Poisson lognormal spatial model to a group of 131 two-lane highway segments in rural areas of Pennsylvania for HSID and compared its ranking performance to three competing models. Four categories of crashes were analyzed which included same-direction, opposite-direction, angle and hit fixed-object. Their results show that the model that considers both multivariate and spatial correlation has the best fit. This study recommended to consider different roadway sites and cross-validate the ranking performance of multivariate spatial model. Apart from the spatial correlations, some researchers explored the serial correlations to benefit from inclusion of factors which are influenced by time (Andrey and Yagar, 1993; Hay and Pettitt, 2001; Wang et al., 2013). Wang et al. (2006) utilized the generalized estimating equations for the temporal analysis of rear-end collisions at intersections. Among different correlation structures, autoregressive (AR) was observed to have best goodness-of-fit and an estimated correlation of 0.4454 for each successive two years. Similar model was employed by Huang et al. (2009) with a time step of one year (lag-1), along with five other models, for empirical evaluation of identification of hotspots by different approaches. Models based on Full Bayesian hierarchical approach were observed to be superior at HSID as well as fitness with actual crash data. Jiang et al. (2014) performed network screening for a highway using site specific fixed-over-time random effect to incorporate temporal correlations into a Poisson lognormal model. For investigation of the impact of weather and time on crash types, El-Basyouny and Kwon (2012) developed four multivariate models using Full Bayesian framework: with and without linear time trend, yearly varying intercept, and yearly varying coefficients. The results confirmed the superiority of the model with varying coefficients to possess the best fit based on DIC.

As evident from the aforementioned studies, unlike spatial models, very limited work exists which goes beyond the comparison of model fitness for models which incorporate the multivariate nature of crash types along with temporal correlations. The primary goal of the present study is to perform a comprehensive cross-validation for five alternate Full Bayesian hierarchical multivariate models which incorporate both spatial as well as temporal correlations among crash outcomes. The competing models are: multivariate poisson log normal spatial, multivariate temporal with linear time trend, multivariate spatial with linear time trend, multivariate temporal with time varying coefficients, and multivariate spatial with time varying coefficients. The inclusion of univariate models was deliberately avoided as the focus of this study is comparison of multivariate models with different random effects. Moreover, previous studies (Lee et al., 2015; Jonathan et al., 2016) have compared univariate and multivariate models and the results demonstrated significant superiority of multivariate ones. This study also demonstrates unique contributions and key differences from Jonathan et al. (2016). First, the study is targeted in analyzing the data of intersections rather than road segments. This would serve as an important addition as intersections are more prone to a diverse nature of crash types due to a variety of reasons (geometric limitations and interaction between pedestrians, bicyclists and vehicles, and so on). Second, instead of treating the data as a singular unit, this study divides crash dataset into two time periods of same size, which allows us to cross validate the relative ranking performances in terms of before and after periods. Third, based on the two subgroups of data, the crash estimation capability of the models is assessed from different perspectives by employing five different cross-validation criteria which includes namely Residual Sum of Squares (RSS), Mean Absolute Deviation (MAD), Kappa, Method Consistency Test (MCT), and Total Rank difference (TRD).