An index for safety management of road networks

Prasad Buddhavarapu and Jorge A Prozzi

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Overview

- Introduction
  - Evolution of the safety management in USA
  - Current issues

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- Proposed methodology
  - Model Specification
  - Efficient Bayesian estimation

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- Implementation example
  - Data description
  - Model results
  - Potential application

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  - Model results
  - Potential application
- Conclusions & Future work

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Introduction

Safety Statistics

National Highway Traffic Safety Administration (NHTSA): occupant fatality rates declined by **22.7%** from 1975 to 1992 which further decreased by **30.3%** by 2010

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Cost of traffic crashes is reportedly more than **two and one-half times** the cost of congestion in urban areas.

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Data-driven or evidence-based.

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1991: Intermodal Surface Transportation Efficiency Act
— Individual states required to develop a Safety Management Systems

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Evolution of the road safety management in USA

2005: Safe, Accountable, Flexible, Efficient Transportation Equity Act
— Establishment of Highway Safety Improvement Program (HSIP).

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2012: Moving Ahead for Progress (MAP-21) Act
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HSIP's data-driven strategic approach to improve highway safety emphasizes

- Need for comprehensive database management systems
- **state-of-the-art data analysis methodologies**

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Goal: To propose

- Computationally efficient Bayesian estimation algorithm
- Safety index for road networks

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Proposed Methods

Model Specification

Sampling model:

$$y_i \sim NB(r, p_i), i \in \{1, 2, ...n\}$$

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Priors & Hyper priors:

$$r \sim Ga(r_0, h); h \sim Ga(a_0, b_0)$$

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Priors & Hyper priors:

$$r \sim Ga(r_0, h); h \sim Ga(a_0, b_0)$$

$$\beta \sim N(b_0, B_0); V_\beta \sim Wishart(\nu, V_0); 1/\tau_c \sim Ga(c_0, d_0)$$

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Proposed Methods

Efficient Bayesian Estimation

Data augmentation allows for constructing analytical conditional posteriors.

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Gibbs sampling algorithm: Iterate t from $1 : M$

- $P(L^{(t)}|r^{(t-1)}, ...)$ — Poisson distribution.
- $P(r^{(t)}|L^{(t)}, ...)$ — Gamma distribution
- $P(\omega_i^{(t)}|\beta_i^{(t-1)}, ...)$ — Polya-Gamma distribution
- $P(\beta_i^{(t)}|\omega^{(t)}, ...)$ — Normal distribution
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NOTE: L & ω are augmented variables.

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Simulation study setup:

Proposed Methods

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- Simulated 2000 crash sites
- Neighborhood based spatial correlation
- Intel i7 1.73Hz processor & 8GB memory

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Simulation results:

- Stationarity attainment in less than 5 minutes, which is significantly faster than existing Metropolis-Hastings based algorithms.
- Parameter estimation accuracy is more than 85%.

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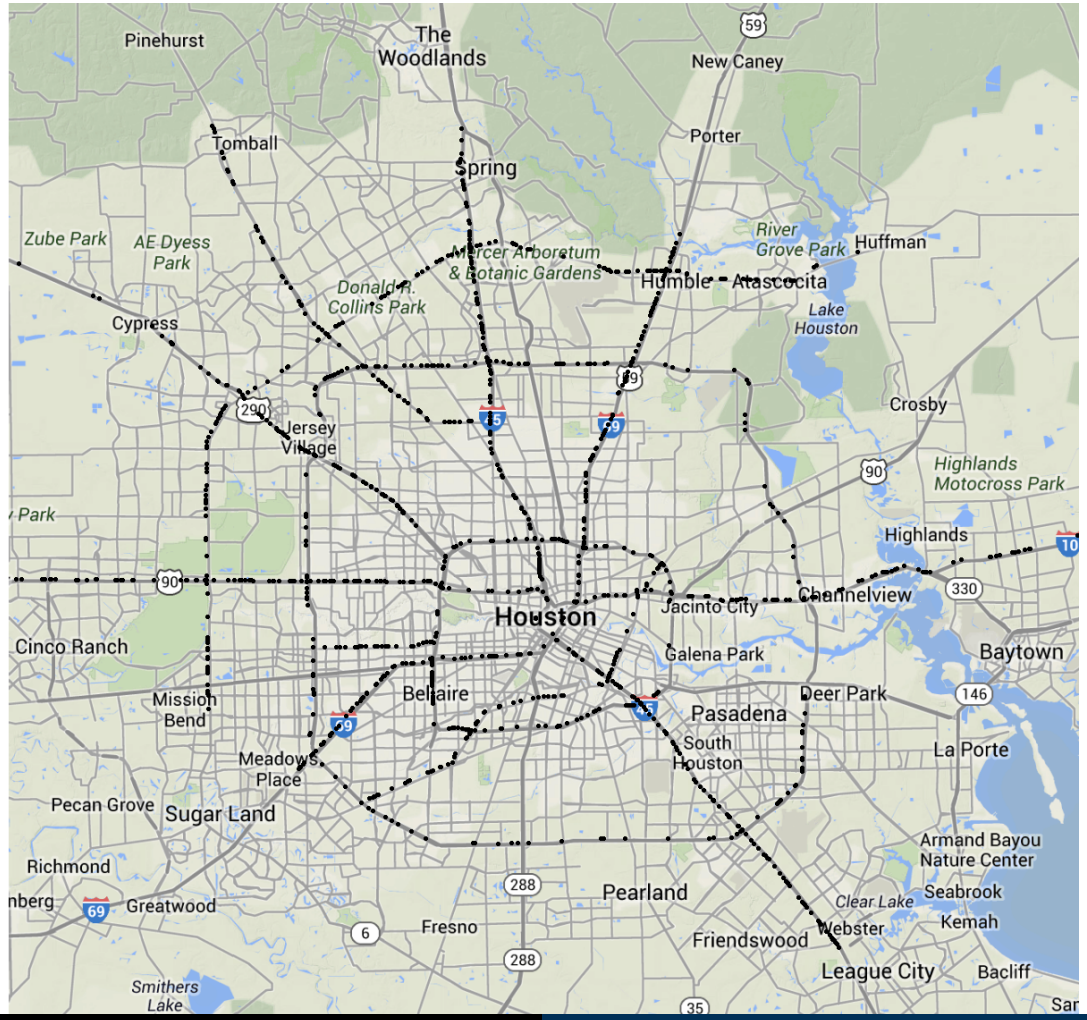
Empirical example

Data description

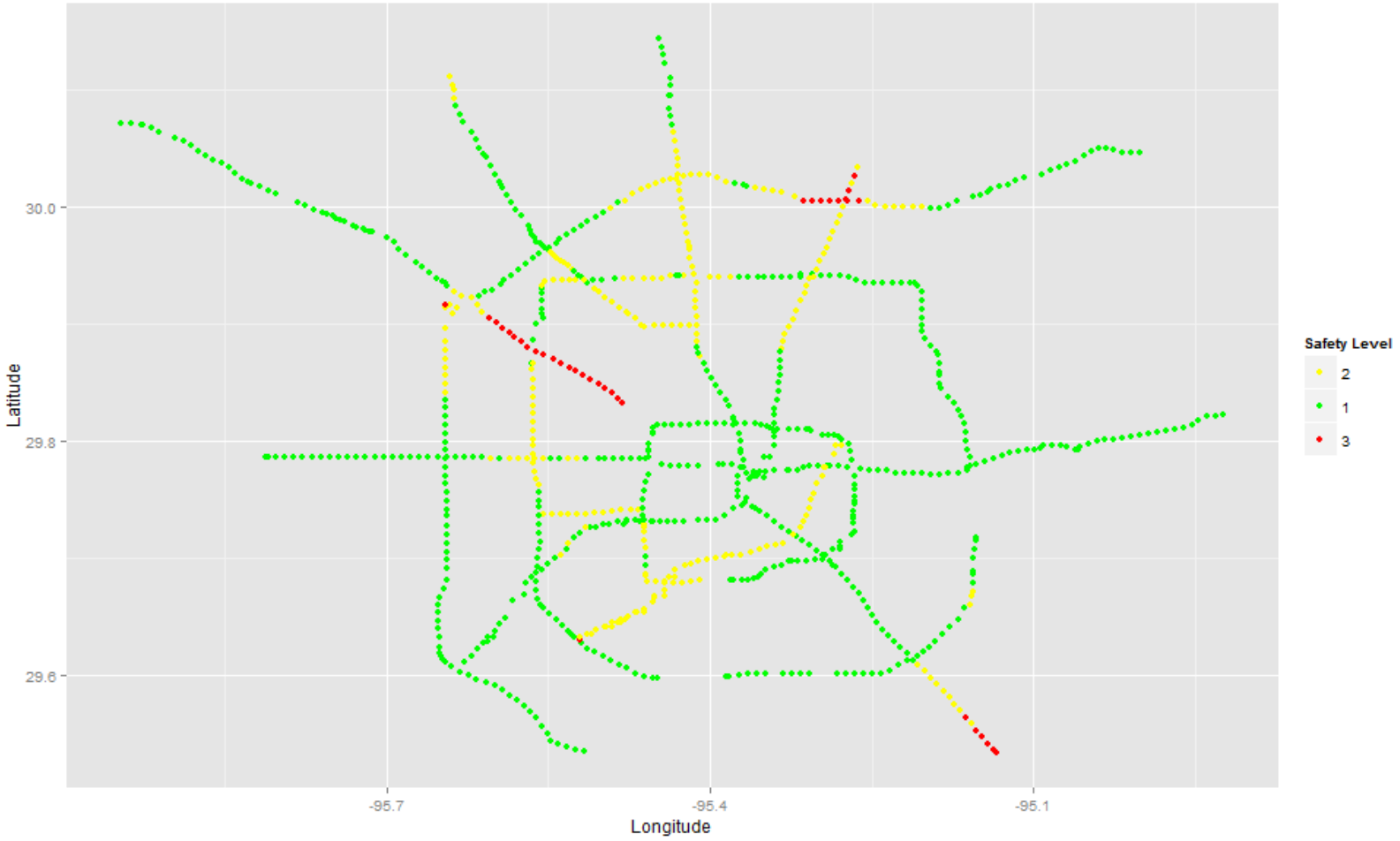
Crash data 10 different routes within Harris county, Texas. Also, included the exposure (traffic) levels in the model.



Empirical example

Potential Application

Posterior means of the proposed safety index or $E(y_i|X_i)$:



Conclusions

Findings

- Framework for extracting useful information from the crash databases and to annually update the crash estimates by accumulating on the prior knowledge.
- Proposed data augmentation scheme enhances the accessibility of the sophisticated Bayesian statistical methods
- *Empirical findings:*
  Roads with smoother ride, higher skid resistance and minor surface distresses are generally associated with the lower crash frequencies.

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Conclusions

Future Work

- Incorporating the probability of ensuring a particular threshold for safety index into the project prioritization applications.
- Current model can be extended to incorporate temporal correlation of the crash counts and correlation across crash severity categories.
- The proposed safety index can be formulated as a economically weighted combination of predicted crash counts of multiple severity levels on a given road segment at any given time.

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Thank You

Questions ?

Contact Information:
Prasad Buddhavarapu
Email:**prasad.buddhavarapu@utexas.edu**
Phone:**+1 512 903 3939**

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