Modeling Truck Safety Critical Events

Efficient Bayesian Hierarchical Statistical and Reliability Models

Miao Cai

Department of Epidemiology and Biostatistics

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SAINT LOUIS UNIVERSITY
COLLEGE FOR PUBLIC HEALTH AND SOCIAL JUSTICE

Dissertation committee

- Chair:
  - Steven E. Rigdon, PhD
- Committee Members:
  - Fadel Megahed, PhD (Farmer School of Business, Miami University)
  - Hong Xian, PhD
- At-large Committee:
  - Kenton Johnson, PhD
  - Juliet Iwelunmor, PhD

1 The problem

Transportation and trucks

Transportation safety deserves attention:

- The 8-th leading cause of death globally in 2016,[1]
- 1.4 million people were killed, mostly aged 4 to 44 years old,[1]
- a loss of 518 billion dollars.[2]

Trucks are the backbone of the economy:

- 70% of freights were delivered by trucks,
- 71.3% of domestic goods and 73.1% of value,[3,4]

Challenges for trucking industry

Drivers:

1. drive alone for long hours,
2. work under time demands, challenging weather and traffic conditions,
3. sleep deprivation and disorders

Trucks:

1. huge weights,
2. large physical dimensions,
3. potentially carry hazardous cargoes.

Truck crash studies

Traditional studies almost exclusively use data that ultimately trace back to **post hoc vehicle inspection**, **interviews** with survived drivers and witnesses, and **police reports**.[5,6]

1. rare events $\rightarrow$ difficulty in estimation,[7]
2. retrospective studies $\rightarrow$ recall bias,[8]
3. crashes are under-reported $\rightarrow$ selection bias.[9,10]

Naturalistic driving studies (NDS)

NDS uses

> ***unobtrusive*** *devices, sensors, and cameras installed on vehicles to* ***proactively*** *collect frequent naturalistic driving behavior and performance data under* ***real-world driving*** *conditions*[5,11]

1. driver-based data, not road segment-based,
2. high-resolution driver behavior and performance data,
3. less costly and difficult per observation.

Safety Critical Events (SCEs)

SCEs are

> *a chain of adverse events following an initial off-nominal event, which can result in an accident if compounded with additional adverse conditions.*[12]

Examples of SCEs are:

1. hard brakes,
2. headways,
3. rolling stability,
4. collision mitigation

The problem

NDSs are relatively *new* and *less studied*. Here are **several problems** in NDS.

1. Are SCEs indicative of real crashes among truck drivers?
2. Can we predict SCEs?
3. How can we innovate existing models to account for features of NDS?

2 Literature review

Association between crashes and SCEs

Examples of studies supporting SCEs:

- hard braking events were significantly associated with collisions and near-crashes,[13]
- a significant positive association between crashes, near crashes, and crash-relevant incidents,[14]
- $\cdots$

Examples of studies that are against SCEs:

- overspeed negatively associated with injury crashes,[15]
- no harm, no validity,[16]
- no demontration on causal link between SCEs and injury crashes.[17]

Gaps:

- Limited number of drivers $\longrightarrow$ less convincing (< 100),
- No studies specifically on truck drivers.

Fatigue

The **most important factor** in transportation safety studies. Fatigue is

> *a multidimensional process that leads to diminished worker performance, which may be a result of prolonged work, psychological, socioeconomic, and environment factors*

- 16.5% of fatal traffic accidents,[18]
- 12.5% of injuries-related collisions,[18],
- 60% of fatal truck crashes.[19]

However, fatigue is hard to measure in transportation safety studies.

- ocular and physiological metrics,
- sleep patterns,
- **cumulative driving time**.

Other risk factors

Four aspects of risk factors are included in previous studies:

- Driver characteristics,
- Weather
- Traffic
- Road features
- · · ·

Gaps in literature:

1. Lack of high-resolution weather and traffic data,
2. No fusion of NDS and API data.

Statistical models

- Logistic regression,
- Poisson regression,
- machine learning models,
- $\cdots$

Gaps in literature:

1. Road-centric models, not driver-centric models,
2. Maximum likelihood estimation (MLE) limited in rare-event models,
3. Lack of recurrent events models.

Bayesian models

In the Bayesian perspective, parameters are viewed as **random variables** that have probability distributions:[20]

$$
\begin{aligned}
p(\theta|\mathbf{X}) &= \frac{p(\theta)p(\mathbf{X}|\theta)}{p(\mathbf{X})} \\
&= \frac{p(\theta)p(\mathbf{X}|\theta)}{\int p(\theta)p(\mathbf{X}|\theta)d\theta}
\end{aligned}
\tag{1}
$$

- $p(\theta)$: subjective priors,
- $p(\mathbf{X}|\theta)$: the likelihood function,
- $p(\mathbf{X}) = \int p(\theta)p(\mathbf{X}|\theta)d\theta$: the normalizing constant, **trickiest** part,
- $p(\theta|\mathbf{X})$: the posterior distribution.

The posterior distribution is a balance between the **prior beliefs** and the **likelihood function**.

Challenges for Bayesian models in a big data setting

Modern Bayesian inferences relies on **Markov chain Monte Carlo (MCMC)** to overcome the intractable denominator issue. However, MCMC is not scalable in the big data setting:

- **Tall data** (a lot of observations),
- **Wide data** (a lot of variables),
- **Correlation between variables** (hierarchical models).[21]

Potential solutions:

- Hamiltonian Monte Carlo,[22]
- Subsampling MCMC such as Energy Conserving Subsampling Hamiltonian Monte Carlo (ECS-HMC).[23]

Conceptual framework

1. *Truck Driver Fatigue Model*,[24]
2. $5\times$ *ST-level hierarchy theory* in traffic safety,[25]
3. *Commercial motor vehicle driver fatigue framework*.[6]

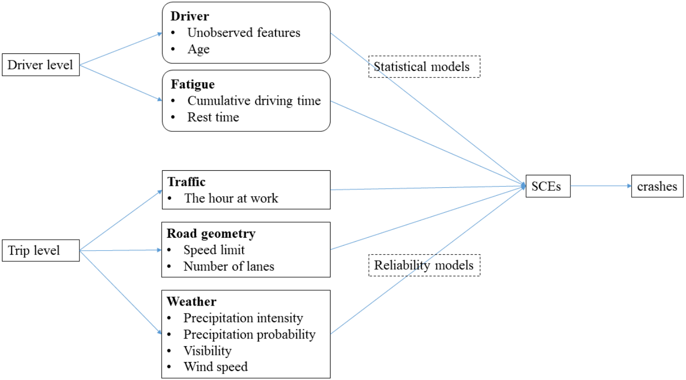

Figure 1: Conceptual model. SCEs represent safety critical events.

3 Research aims

Overall aim

Gaps in previous literature:

1. The association between crashes and SCEs has not been confirmed among truck drivers,
2. Difficulty in fusing high-resolution NDS and API data,
3. Bayesian inference is not scalable in tall and wide NDS data setting,
4. Recurrent events models were not widely applied in NDS data.

The overarching goal of this proposed dissertation is to construct **scalable Bayesian hierarchical models** for NDS data and understand how **cumulative driving time** and other environmental factors will impact the performance of truck drivers.

Aim 1

To examine the association between truck crashes and SCEs using a Bayesian Gamma-Poisson regression.

I hypothesize that the rate of crashes is positively associated with the rate of SCEs among the truck drivers controlling for the miles driven and other covariates.

Aim 2

To construct three scalable Bayesian hierarchical models to identify potential risk factors for SCEs.

I hypothesize that the patterns of SCEs vary significantly from drivers to drivers and can be predicted using cumulative driving time, weather, road geometry, driver's age, and other factors}.

- 2a) Bayesian hierarchical **logistic** regression,
- 2b) Bayesian hierarchical **Poisson** regression,
- 2c) Bayesian hierarchical **non-homogeneous Poisson process (NHPP)** with the power law process (PLP) intensity function.

Aim 3

> *To propose an innovative reliability model that accounts for both within shift cumulative driving time and between-trip rest time.*

I hypothesize that **between-trip rest time** can **recover** the intensity function by some proportion κ, and intensity function varies significantly from drivers to drivers.

4 Data

Data sources

1. **Real-time ping**: vehicle number, date and time, latitude, longitude, driver identification number (ID), and speed at that second (every 2-10 minutes), ~1.4 billion pings (150 GB `.csv` file),
2. **Truck crashes and SCEs**: hard brakes, headways, and rolling stability were collected if kinematic thresholds were met,
3. **Driver demographics**: age,
4. **Weather from the DarkSky API** (500 drivers): precipitation intensity, precipitation probability, wind speed, and visibility,
5. **Road geometry from the OpenStreetMap** (500 drivers): speed limits and the number of lanes.

Demonstration of data I

Table 1: A demonstration of ping data

trip_id	ping_time	speed	latitude	longitude	driver
100160724	2015-10-23 08:09:26	5	33.94288	-118.1681	canj1
100160724	2015-10-23 08:22:58	4	33.97146	-118.1677	canj1
100160724	2015-10-23 08:23:12	8	33.97178	-118.1677	canj1
100160724	2015-10-23 08:23:30	4	33.97233	-118.1678	canj1
100160724	2015-10-23 08:38:00	40	34.00708	-118.1798	canj1

Demonstration of data II

Table 2: A demonstration of safety critical events

driver	event_time	event_type
canj1	2015-10-23 14:46:08	HB
canj1	2015-10-26 15:06:03	HB
canj1	2015-10-28 11:58:24	HB
canj1	2015-10-28 17:42:36	HB
canj1	2015-11-02 07:13:56	HB

Demonstration of data III

Table 3: A demonstration of crashes table

Accident ID	Open date	Open time	Driver	Type	Cause	N_injuries	Fatalities
I1417883	2014-06-10	22:00:00	gres0	L13	99	0	0
I1418899	2014-06-18	10:52:00	gres0	L13	1	0	0
I1430678	2014-10-02	13:38:00	gres0	L13	1	0	0
I1427445	2014-09-04	19:46:00	gres0	L13	1	0	0
I1429286	2014-09-22	05:00:00	gres0	L13	1	0	0
I1432924	2014-10-23	07:00:00	gres0	L25	1	0	0
15384570	2015-11-04	13:01:00	canj1	L70	3	0	0

Demonstration of data IV

Table 4: A demonstration of drivers table

driver	age
canj1	46
farj7	54
gres0	55
hunt	48
kell0	51

Table 5: A demonstration of weather data from the DarkSky API

ping_time	latitude	longitude	precip_intensity	precip_probability	wind_speed	visibility
2015-10-23 08:09:26	33.94288	-118.1681	0	0	0.21	9.82
2015-10-23 08:22:58	33.97146	-118.1677	0	0	0.22	9.81
2015-10-23 08:23:12	33.97178	-118.1677	0	0	0.22	9.81
2015-10-23 08:23:30	33.97233	-118.1678	0	0	0.22	9.81
2015-10-23 08:38:00	34.00708	-118.1798	0	0	0.24	9.81

Demonstration of data V

Table 6: A demonstration of road geometry data from the OpenStreetMap API

driver	latitude	longitude	speed_limit	num_lanes
farj7	30.32650	-89.86389	65	2
farj7	30.34032	-91.73116	65	2
farj7	30.34174	-91.72572	60	2
farj7	30.35075	-91.69085	60	2
farj7	30.35165	-91.68755	60	2

Data aggregation

1. **Trip**: for each of the truck drivers, if the real-time ping data showed that the truck was not moving for more than 20 minutes, the ping data will be separated into two different trips (~200,000 rows),
2. **30-minute intervals**: as the length of a trip can vary significantly from 5 minutes to more than 8 hours, I will transform the trips data into standardized 30-minute fixed intervals according to the starting and ending time of trips (~1 million rows),
3. **Shift**: the trips data will be further divided into different shifts if the specific driver was not moving for eight hours.

Table 1: ping data

trip_id	ping_time	speed	latitude	longitude	driver
100160724	2015-10-23 08:09:26	5	33.94288	-118.1681	canj1
100160724	2015-10-23 08:22:58	4	33.97146	-118.1677	canj1
100160724	2015-10-23 08:23:12	8	33.97178	-118.1677	canj1
100160724	2015-10-23 08:23:30	4	33.97233	-118.1678	canj1
100160724	2015-10-23 08:38:00	40	34.00708	-118.1798	canj1
100160725	2015-10-23 09:04:24	16	34.00733	-118.1844	canj1
100160725	2015-10-23 09:08:00	16	34.00984	-118.1939	canj1
100160725	2015-10-23 09:08:00	16	34.00982	-118.1938	canj1
100160725	2015-10-23 09:08:08	23	34.01016	-118.1949	canj1
100160725	2015-10-23 09:08:10	25	34.01024	-118.1951	canj1
100160725	2015-10-23 09:08:10	25	34.01024	-118.1951	canj1
100160725	2015-10-23 09:08:24	21	34.01068	-118.1964	canj1
100160725	2015-10-23 09:22:56	4	33.99253	-118.1747	canj1
100160725	2015-10-23 09:23:12	2	33.99271	-118.1748	canj1
100160725	2015-10-23 09:23:38	9	33.99325	-118.1753	canj1
100160725	2015-10-23 09:29:20	0	33.99440	-118.1758	canj1
100160725	2015-10-23 09:38:10	0	33.99441	-118.1758	canj1
100160725	2015-10-23 09:43:02	9	33.99371	-118.1757	canj1
100160725	2015-10-23 09:52:22	6	33.98915	-118.1619	canj1
100160725	2015-10-23 09:53:12	8	33.98912	-118.1616	canj1

Table 2: Transformed trips data

driver	trip_id	start_time	end_time	trip_time	distance
canj1	100160724	2015-10-23 08:09:26	2015-10-23 08:37:26	28	4.473
canj1	100160725	2015-10-23 09:04:24	2015-10-23 11:21:24	137	46.721
canj1	100160726	2015-10-23 12:00:36	2015-10-23 15:37:36	217	164.576
canj1	100160727	2015-10-23 16:38:10	2015-10-23 18:37:10	119	52.907
canj1	100160728	2015-10-26 07:49:04	2015-10-26 10:52:04	183	104.085

Table 3: Transformed 30-minute intervals

driver	interval_id	start_time	end_time	interval_time	distance
canj1	197089	2015-10-23 08:09:26	2015-10-23 08:38:00	28	4.538
canj1	197090	2015-10-23 09:04:24	2015-10-23 09:34:24	30	2.645
canj1	197091	2015-10-23 09:34:24	2015-10-23 10:04:24	30	0.984
canj1	197092	2015-10-23 10:04:24	2015-10-23 10:34:24	30	5.928
canj1	197093	2015-10-23 10:34:24	2015-10-23 11:04:24	30	17.348

Table 4: Transformed shifts data

driver	shift_ID	shift_start	shift_end	shift_length
canj1	1	2015-10-23 08:09:26	2015-10-23 18:37:56	628
canj1	2	2015-10-26 07:49:04	2015-10-26 15:06:58	437
canj1	3	2015-10-27 01:59:48	2015-10-27 07:58:56	359
canj1	4	2015-10-28 08:05:08	2015-10-28 20:20:32	735
canj1	6	2015-10-30 09:27:12	2015-10-30 21:18:22	711

Table 5: safety critical events

driver	event_time	event_type
canj1	2015-10-23 14:46:08	HB
canj1	2015-10-26 15:06:03	HB
canj1	2015-10-28 11:58:24	HB
canj1	2015-10-28 17:42:36	HB
canj1	2015-11-02 07:13:56	HB

Table 6: drivers

driver	age
canj1	46
farj7	54
gres0	55
hunt	48
kell0	51
lewr10	27
rice30	34
smiv	49
sunc	37
woow59	24

Table 7: Road geometry from the OpenStreetMap API

driver	latitude	longitude	speed_limit	num_lanes
farj7	30.32650	-89.86389	65	2
farj7	30.34032	-91.73116	65	2
farj7	30.34174	-91.72572	60	2
farj7	30.35075	-91.69085	60	2
farj7	30.35165	-91.68755	60	2

Table 8: weather from the DarkSky API

ping_time	latitude	longitude	precip_intensity	precip_probability	wind_speed	visibility
2015-10-23 08:09:26	33.94288	-118.1681	0	0	0.21	9.82
2015-10-23 08:22:58	33.97146	-118.1677	0	0	0.22	9.81
2015-10-23 08:23:12	33.97178	-118.1677	0	0	0.22	9.81
2015-10-23 08:23:30	33.97233	-118.1678	0	0	0.22	9.81
2015-10-23 08:38:00	34.00708	-118.1798	0	0	0.24	9.81

Data demonstration I

Table 7: 30 minutes intervals data for hierarchical logistic and Poisson regression

driver	start_time	end_time	interval_time	distance
canj1	2015-10-23T08:09:26Z	2015-10-23T08:38:00Z	28	4.538
canj1	2015-10-23T09:04:24Z	2015-10-23T09:34:24Z	30	2.645
canj1	2015-10-23T09:34:24Z	2015-10-23T10:04:24Z	30	0.984
canj1	2015-10-23T10:04:24Z	2015-10-23T10:34:24Z	30	5.928
canj1	2015-10-23T10:34:24Z	2015-10-23T11:04:24Z	30	17.348

Data demonstration II

Table 8: shifts data for hierarchical non-homogeneous Poisson process

driver	start_time	end_time	shift_length	n_SCE	SCE_time	SCE_type
canj1	2015-10-23T08:09:26Z	2015-10-23T18:37:56Z	628	1	2015-10-23 14:46:08	HB
canj1	2015-10-26T07:49:04Z	2015-10-26T15:06:58Z	437	1	2015-10-26 15:06:03	HB
canj1	2015-10-27T01:59:48Z	2015-10-27T07:58:56Z	359	0	NA	NA
canj1	2015-10-28T08:05:08Z	2015-10-28T20:20:32Z	735	2	2015-10-28 11:58:24;2015-10-28 17:42:36	HB;HB
canj1	2015-10-30T09:27:12Z	2015-10-30T21:18:22Z	711	0	NA	NA

Table 9: SCEs data for hierarchical non-homogeneous Poisson process

driver	shift_ID	start_time	event_time	shift_length	time2event
canj1	1	2015-10-23 08:09:26	2015-10-23 14:46:08	10.467	6.600
canj1	2	2015-10-26 07:49:04	2015-10-26 15:06:03	7.283	7.267
canj1	4	2015-10-28 08:05:08	2015-10-28 11:58:24	12.250	3.883
canj1	4	2015-10-28 08:05:08	2015-10-28 17:42:36	12.250	9.617
canj1	7	2015-11-02 06:26:48	2015-11-02 07:13:56	13.667	0.783

5 Methods

Aim 1 - Data and variables

The first aim seeks to determine the association between the rate of crashes and the rate of SCEs at the level of drivers.

- **Data**:
  - over 50,000 commercial truck drivers,
  - 1,494,678,173 pings,
  - 35,008 crashes, 480,331 SCEs
- **outcome variable**: the number of crashes for each driver.
- **The primary independent variable**: the number of SCEs per 10,000 miles. These SCEs will be further decomposed into the number of hard brakes, headways, and rolling stability per 10,000 miles in similar analysis.
- **The covariates**: the total miles driven, the percent of night driving, and the age of the drivers.

Aim 1 - Gamma-Poisson model

Here is how the proposed Gamma-Poisson model will be implemented. Let us assume that:

$$\lambda \sim \text{Gamma}(\alpha, \beta)$$
$$X|\lambda \sim \text{Poisson}(\lambda)$$

Then we have:

$$X \sim \text{Gamma-Poisson}(\alpha, \beta)$$

The Gamma-Poisson distribution is a α-parameter distribution. The log-linear Gamma-Poisson model will be specified as:

$$\log \beta = \mathbf{X}\gamma - \log m,$$

- $\mathbf{X}$ is the predictor variables matrix, including age, gender, mean speed, business unit, and driver types,
- γ is the associated $2 * 1$ parameter vector,
- m: is the total miles driven as an offset term,
- α: a fixed overdispersion parameter.

Aim 1 - potential problems and alternative plans

The sheer size of the original ping data may be a problem in aim 1: the ping data has 1,494,678,173 rows and 9 columns, (>140 gigabytes (GB) `.csv`).

Although I will use the OSC server that has Random-Access Memory (RAM) of more than 500 GB, it may still be hard to read and process this giant file.

1. If the OSC server cannot handle the data correctly, I will separate the single giant csv file into **several small csv files** according to driver ID, then aggregate the pings to trips for each small csv file.
2. After the ping data are aggregated to trips, it is unlikely that the log-linear Gamma-Poisson model fail. In that unlikely event, I can turn to **negative binomial models** or use **traditional MLE estimates** instead of Bayesian estimation.

Aim 2 Overview

*The purpose of aim 2 is to develop three **scalable hierarchical Bayesian statistical and reliability models** for the SCEs of truck drivers and identify potential risk factors.*

- **Data**: 30-minute intervals for 496 drivers,
- **Outcome**:
  - whether SCEs occurred or not (binary variable),
  - the number of SCEs (count variable),
  - the time to each SCE (in minutes),
- **Predictors**:
  - driver-level random-effects,
  - age,
  - cumulative driving time,
  - weather,
  - road geometry,
  - mean speed,
  - speed variation,

Aim 2a) Bayesian hierarchical logistic regression

Two-level model: 1) 30-minute interval level i, 2) driver level $d(i)$.

$$
\begin{aligned}
Y_i &\sim \text{Bernoulli}(p_i) \\
\log \frac{p_i}{1 - p_i} &= \beta_{0,d(i)} + \beta_{1,d(i)} \cdot \text{CT}_i + \sum_{j=1}^{J} x_{ij}\beta_j \\
\beta_{0,d} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2), \quad d = 1, 2, \cdots, D \\
\beta_{1,d} &\sim \text{i.i.d. } N(\mu_1, \sigma_1^2), \quad d = 1, 2, \cdots, D
\end{aligned}
\tag{2}
$$

- Y_i: whether SCEs occurred in the 30-minute interval or not (binary),
- $\beta_{0,d(i)}$: random intercepts for each driver, $\beta_{1,d(i)}$ is random slopes for cumulative driving time CT_i,
- $\beta_2, \beta_3, \cdots, \beta_J$: fixed parameters for covariates x_{ij}.
- μ_0, σ_0: hyper-parameters for random intercepts $\beta_{0,d}$,
- μ_1, σ_1: hyper-parameters for random slopes $\beta_{1,d}$.

Aim 2a) Priors

Since we do not have much prior knowledge on the parameters, I will assign weakly informative priors[26] for these parameters:

$$
\begin{aligned}
\mu_0 &\sim N(0, 5^2) \\
\mu_1 &\sim N(0, 5^2) \\
\sigma_0 &\sim \text{Gamma}(1, 1) \\
\sigma_1 &\sim \text{Gamma}(1, 1) \\
\beta_2, \beta_3, \cdots, \beta_J &\sim N(0, 10^2)
\end{aligned} \tag{3}
$$

The priors for the hyperpriors need to be relatively more restrictive than priors for fixed-effects parameters $\beta_2, \beta_3, \cdots, \beta_J$[20].

Aim 2b) Model 2: Bayesian hierarchical Poisson regression

Two-level model: 1) 30-minute interval level i, 2) driver level $d(i)$.

$$\begin{aligned}
N_i &\sim \text{Poisson}(T_i \cdot \lambda_i) \\
\log \lambda_i &= \beta_{0,d(i)} + \beta_{1,d(i)} \cdot \text{CT}_i + \sum_{j=1}^{J} x_{ij}\beta_j \\
\beta_{0,d} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2), \quad d = 1, 2, \cdots, D \\
\beta_{1,d} &\sim \text{i.i.d. } N(\mu_1, \sigma_1^2), \quad d = 1, 2, \cdots, D
\end{aligned} \tag{4}$$

- Y_i: the number of SCEs occurred in the 30-minute interval,
- T_i: length of the 30-minute interval,
- The other components are the same as those in hierarchical logistic regression.

The scalable Bayesian statistical and reliability models will be conducted using the **HMC-ECS algorithm** (self-defined functions in `Python 3.6.0`) or **HMC** (the `rstan` package in statistical computing environment `R 3.6.0`)[23,27,28].

Aim 2c) motivation for recurrent event models

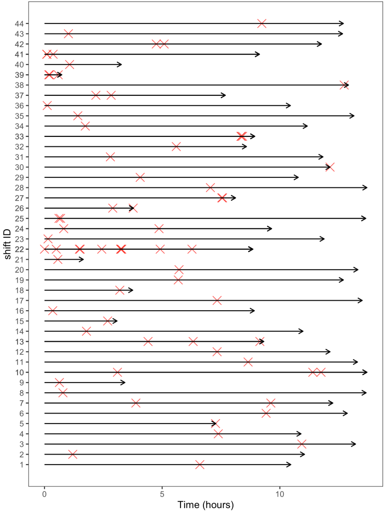

Figure 2: An arrow plot of time to SCEs in each shift

Aim 2c) Theories on NHPP and PLP

Nonhomogeneous Poisson Process (NHPP):

a Poisson process whose intensity function is non-constant.

Power law process (PLP): a NHPP with the intensity function of:

$$\lambda(t) = \frac{\beta}{\theta}\left(\frac{t}{\theta}\right)^{\beta-1}, \quad \beta > 0, \theta > 0 \tag{5}$$

- $\beta > 1$: intensity increasing $\rightarrow$ reliability deteriorating,
- $\beta = 1$: constant intensity $\rightarrow$ reliability not changing,
- $\beta < 1$: intensity decreasing $\rightarrow$ reliability improving,
- θ: scale parameter.

There are two forms of truncation in a NHPP:

1. *Failure truncation*: when testing stops after a predetermined number of failures,
2. *Time truncation*: when testing stops at a predetermined time t.

Aim 2c) Intensity function of NHPP

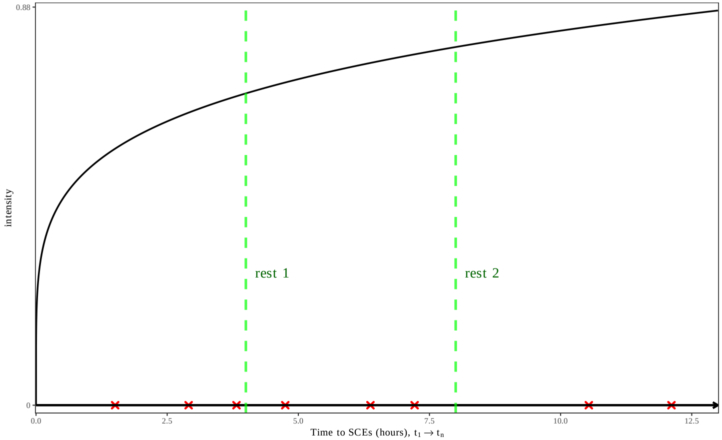

Figure 3: Intensity function, time to SCEs, and rest time within a shift generated from a NHPP with a PLP intensity function, $\beta = 1.2, \theta = 2$

Aim 2c) Notations

Let $T_{d,s,i}$ denotes the time to the d-th driver's s-th shift's i-th critical event. The total number critical events of d-th driver's s-th shift is $n_{d,s}$. The ranges of these notations are:

- $i = 1, 2, \cdots, n_{d,S_d}$: SCE ID,
- $s = 1, 2, \cdots, S_d$: shift ID,
- $d = 1, 2, \cdots, D$: driver ID.

Aim 2c) Bayesian hierarchical NHPP with PLP intensity function

Assume the time to SCEs within the d-th driver's s-th shift were generated from a PLP, with a fixed shape parameter β and varying scale parameters $\theta_{d,s}$ across drivers d and shifts s.

$$\begin{aligned}
T_{d,s,1}, T_{d,s,2}, \cdots, T_{d,s,n_{d,s}} &\sim \text{PLP}(\beta, \theta_{d,s}) \\
\beta &\sim \text{Gamma}(1,1) \\
\log \theta_{d,s} &= \gamma_{0d} + \gamma_1 x_{d,s,1} + \gamma_2 x_{d,s,2} + \cdots + \gamma_k x_{d,s,k} \\
\gamma_{01}, \gamma_{02}, \cdots, \gamma_{0D} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2) \\
\gamma_1, \gamma_2, \cdots, \gamma_k &\sim \text{i.i.d. } N(0, 10^2) \\
\mu_0 &\sim N(0, 10^2) \\
\sigma_0 &\sim \text{Gamma}(1,1)
\end{aligned} \tag{6}$$

The shape parameter β shows the reliability changes of drivers:

- $\beta > 1$: intensity increasing $\rightarrow$ reliability deteriorating,
- $\beta = 1$: constant intensity $\rightarrow$ reliability not changing,
- $\beta < 1$: intensity decreasing $\rightarrow$ reliability improving,

Aim 2c) Potential problems and alternative plans

The sheer size of the 30-minute interval table and merged shifts table may be a problem in this aim.

- The 30-minute interval table: ~one million rows and 10 variables,
- Merged shift table: ~200,000 rows and 10 variables.
- 496 random intercepts and slopes

Although I propose to use the HMC-ECS to estimate the random effect, there are still chances that the model does not work. In that case, I will **sample 50 to 200 typical drivers**, then conduct the analysis based on this smaller sample data. In the unlikely event that the models still fails based on this smaller data, I can restrict the hierarchical models to **random intercepts only model** or use **traditional MLE** instead of Bayesian estimation.

Aim 3

> *Aim 3 seeks to innovate the NHPP with a PLP intensity function proposed in Aim 2 by adding one more parameter κ.*

I propose to account for the rest time within a shift by adding one more parameter κ, **the percent of reliability recovery** for each a break within a shift.

This new reliability model (**jump-point PLP (JPLP)**) will be between a *NHPP* where the intensity function is not influenced by between-trip rests ("as bad as old"), and a *renewal process* where the intensity function is fully recovered by between-trip rests ("as good as new").

Aim 3 - intensity function of NHPP

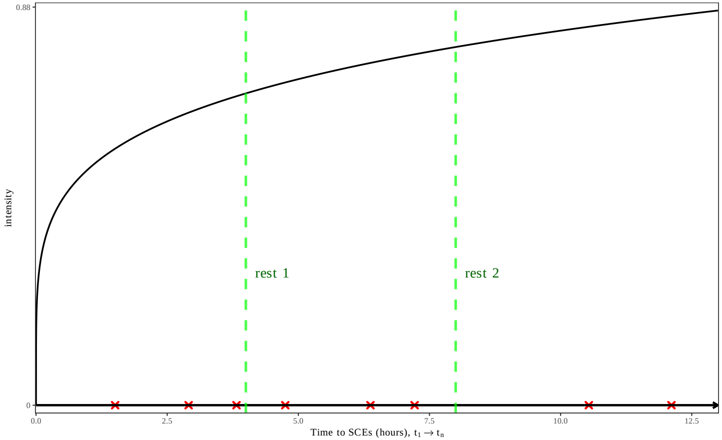

Figure 4: Intensity function, time to SCEs, and rest time within a shift generated from a NHPP with a PLP intensity function, $\beta = 1.2$, $\theta = 2$

Aim 3 - intensity function of proposed jump-point PLP (JPLP)

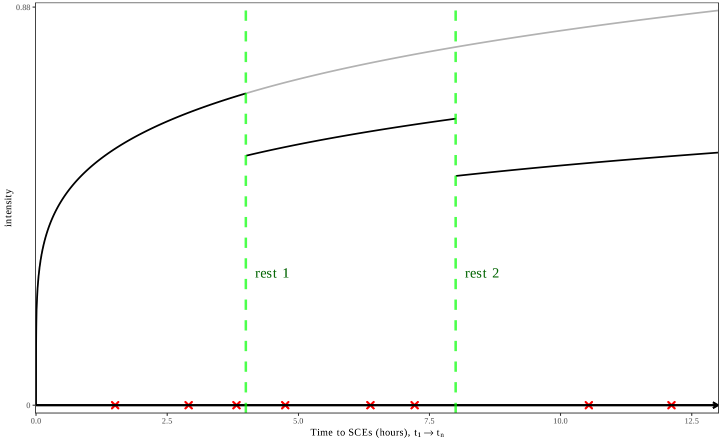

Figure 5: Intensity function, time to SCEs, and rest time within a shift with a jump-point PLP intensity function, $\beta = 1.2$, $\theta = 2$, $\kappa = 0.8$

Aim 3 - JPLP

JPLP: **an added parameter** κ based on Bayesian hierarchical PLP.

$$
\begin{aligned}
T_{d,s,1}, T_{d,s,2}, \cdots, T_{d,s,n_{d,s}} &\sim \text{JPLP}(\beta, \theta_{d,s}, \kappa) \\
\beta &\sim \text{Gamma}(1, 1) \\
\log \theta_{d,s} &= \gamma_{0d} + \gamma_1 x_{d,s,1} + \gamma_2 x_{d,s,2} + \cdots + \gamma_k x_{d,s,k} \\
\kappa &\sim \text{Uniform}(0, 1) \\
\gamma_{01}, \gamma_{02}, \cdots, \gamma_{0D} &\sim \text{i.i.d. } N(\mu_0, \sigma_0^2) \\
\gamma_1, \gamma_2, \cdots, \gamma_k &\sim \text{i.i.d. } N(0, 10^2) \\
\mu_0 &\sim N(0, 5^2) \\
\sigma_0 &\sim \text{Gamma}(1, 1)
\end{aligned}
\tag{7}
$$

- β: shape parameter that reflects the reliability changes of drivers,
- $\theta_{d,s}$: a scale parameter,
- κ: **the percent of intensity function recovery** once the driver takes a break.

Aim 3 - potential problems and alternative plans

In the unlikely event that the JPLP fails to be models, I will use the **modulated PLP** proposed by Black and Rigdon (1996)[29]. The modulated PLP has well-defined data generating process, intensity function, and likelihood functions. If the JPLP does not work, I will revise the modulated PLP into **a hierarchical modulated PLP**.

The hierarchical JPLP and hierarchical modulated PLP will be estimated using `Stan` programs by adding self-defined likelihood function, which can be accessed via the `rstan` package in statistical computing environment R 3.6.0 on the OSC[27,28,30].

Conclusion and implications

- This work will illustrate the relationship between crashes and SCEs,
- The work will provide estimates of cumulative driving time on the risk of SCEs,
- The proposed JPLP will be an innovative reliability model for NDS datasets,
- The fusion of high-resolutional API and NDS data sets is an exciting opportunity,
- The subsampling MCMC can be a useful solution for wide and long NDS datasets.

References I

1 WHO. The top 10 causes of death. 2018.

2 Dalal K, Lin Z, Gifford M, Svanström L. Economics of global burden of road traffic injuries and their relationship with health system variables. *International journal of preventive medicine* 2013; **4**: 1442.

3 Olson R, Wipfli B, Thompson SV *et al.* Weight control intervention for truck drivers: The shift randomized controlled trial, united states. *American journal of public health* 2016; **106**: 1698–706.

4 Anderson JR, Ogden JD, Cunningham WA, Schubert-Kabban C. An exploratory study of hours of service and its safety impact on motorists. *Transport Policy* 2017; **53**: 161–74.

5 Hickman JS, Hanowski RJ, Bocanegra J. A synthetic approach to compare the large truck crash causation study and naturalistic driving data. *Accident Analysis & Prevention* 2018; **112**: 11–4.

6 Stern HS, Blower D, Cohen ML *et al.* Data and methods for studying commercial motor vehicle driver fatigue, highway safety and long-term driver health. *Accident Analysis & Prevention* 2019; **126**: 37–42.

References II

7 Theofilatos A, Yannis G, Kopelias P, Papadimitriou F. Impact of real-time traffic characteristics on crash occurrence: Preliminary results of the case of rare events. *Accident Analysis & Prevention* 2018.

8 Girotto E, Andrade SM de, González AD, Mesas AE. Professional experience and traffic accidents/near-miss accidents among truck drivers. *Accident Analysis & Prevention* 2016; **95**: 299–304.

9 Ye F, Lord D. Investigation of effects of underreporting crash data on three commonly used traffic crash severity models: Multinomial logit, ordered probit, and mixed logit. *Transportation Research Record* 2011; **2241**: 51–8.

10 Savolainen PT, Mannering FL, Lord D, Quddus MA. The statistical analysis of highway crash-injury severities: A review and assessment of methodological alternatives. *Accident Analysis & Prevention* 2011; **43**: 1666–76.

11 Guo F. Statistical methods for naturalistic driving studies. *Annual review of statistics and its application* 2019; **6**: 309–28.

References III

12 Saleh JH, Saltmarsh EA, Favaro FM, Brevault L. Accident precursors, near misses, and warning signs: Critical review and formal definitions within the framework of discrete event systems. *Reliability Engineering & System Safety* 2013; **114**: 148–54.

13 Dingus TA, Klauer SG, Neale VL *et al.* The 100-car naturalistic driving study. Phase 2: Results of the 100-car field experiment. United States. Department of Transportation. National Highway Traffic Safety ..., 2006.

14 Wu K-F, Aguero-Valverde J, Jovanis PP. Using naturalistic driving data to explore the association between traffic safety-related events and crash risk at driver level. *Accident Analysis & Prevention* 2014; **72**: 210–8.

15 Gitelman V, Bekhor S, Doveh E, Pesahov F, Carmel R, Morik S. Exploring relationships between driving events identified by in-vehicle data recorders, infrastructure characteristics and road crashes. *Transportation research part C: emerging technologies* 2018; **91**: 156–75.

16 Knipling RR. Naturalistic driving events: No harm, no foul, no validity. 2015.

17 Knipling RR. Threats to scientific validity in truck driver hours-of-service studies. 2017.

18 American Automobile Association Foundation for Traffic Safety. Asleep at the Wheel: The Prevalence and Impact of Drowsy Driving. 2010.

References IV

19 Cavuoto L, Megahed F. Understanding fatigue: Implications for worker safety. *Professional Safety* 2017; **62**: 16–9.

20 Gelman A, Stern HS, Carlin JB, Dunson DB, Vehtari A, Rubin DB. Bayesian data analysis. Chapman; Hall/CRC, 2013.

21 Kruschke JK, Vanpaemel W. Bayesian estimation in hierarchical models. *The Oxford handbook of computational and mathematical psychology* 2015;: 279–99.

22 Betancourt M. A conceptual introduction to hamiltonian monte carlo. *arXiv preprint arXiv:170102434* 2017.

23 Dang K-D, Quiroz M, Kohn R, Tran M-N, Villani M. Hamiltonian monte carlo with energy conserving subsampling. *Journal of Machine Learning Research* 2019; **20**: 1–31.

24 Crum MR, Morrow PC. The influence of carrier scheduling practices on truck driver fatigue. *Transportation Journal* 2002;: 20–41.

25 Huang H, Abdel-Aty M. Multilevel data and bayesian analysis in traffic safety. *Accident Analysis & Prevention* 2010; **42**: 1556–65.

26 Gelman A, Simpson D, Betancourt M. The prior can often only be understood in the context of the likelihood. *Entropy* 2017; **19**: 555.

References V

27 Stan Development Team. RStan: The R interface to Stan. 2018. http://mc-stan.org/.

28 R Core Team. R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing, 2018 https://www.R-project.org/.

29 Black SE, Rigdon SE. Statistical inference for a modulated power law process. *Journal of Quality Technology* 1996; **28**: 81–90.

30 Center OS. Ohio supercomputer center. 1987. http://osc.edu/ark:/19495/f5s1ph73.