A real-time crash risk estimation framework for signalized intersections
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Presenter
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Background

- In Australia, **1195 people killed** and **39,330 hospitalised** annually (BITRE 2019)

- Social cost of road crashes = **$29.7 billion** (BITRE 2009) ≈1.3% of Australia’s GDP
Challenges in Road Safety Analysis

Reactive Crash-based Analysis

Crash Occurred in 2014

Analysis done in 2019

Implementation?

Proactive Conflict-based Analysis

Conflict Observed...

...Rapid Analysis

Ready for Action!
Traffic Conflicts:
Dangerous traffic interactions, potential road crashes

Road Crashes:
End results of traffic conflicts

Courtesy: LJ Raggy (https://www.youtube.com/watch?v=Xx7NCbzIxI)

QUT
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Smart Transport Safety Research Lab
Safety Pyramid of Traffic Events

- Crashes
- Serious Traffic Conflicts
- Light Traffic Conflicts
- Normal Interactions
- Undisturbed Passages
Crashes (unobserved extremes) can be estimated from traffic conflicts (observed extremes) with an appropriate modelling technique.
Objective

To develop a real-time crash risk estimation framework using traffic conflicts

➢ How can Extreme Value Theory be leveraged to obtain real-time crash risk?

➢ How crash risk varies with different time periods of the day (e.g., peak vs. off-peak hours)?

➢ Does incorporating a covariate in the model yield better fit and crash estimates?
Methodology

➔ Extreme Value Theory to model traffic extremes at the signal cycle level

➔ Given that $z_{ij}$ corresponds to the maximum value of a traffic conflict indicator for cycle $i$ at site $j$, a GEV distribution function can be written as

$$G(z_{ij} < z|\mu_{ij}, \phi_{ij}, \xi_{ij}) = \exp\left(-\left[1 + \xi_{ij}\left(\frac{z - \mu_{ij}}{\exp(\phi_{ij})}\right)^{-1/\xi_{ij}}\right]\right)$$

where $\mu$, $\sigma$, and $\xi$ represents location, scale ($\phi = log\sigma$), and shape parameters
Data Collection

Video recording of traffic movements at intersections
Data Collection

A total of 96 hours of traffic videos from a four-legged signalized intersection in Brisbane, Australia
AI-based Traffic Conflict Data Extraction

1. Setting up cameras at vantage points
2. Video observation of targeted traffic
3. Camera calibration and homography matrix
4. Road user detection using Yolo-v4.0
5. Road user tracking using DeepSORT
6. Extracting traffic conflicts

(all interactions with time-to-collision ≤ 3 s)
Advanced Mobility Analytics Group (AMAG)
AI-based Traffic Conflict Data Extraction
Traffic conflict indicator

Modified time-to-collision (MTTC)

\[ MTTC = \frac{\Delta s \pm \sqrt{\Delta s^2 + 2 \Delta a (x_{LV} - x_{FV} - D_{LV})}}{\Delta a}, \]

\( \Delta s = \) relative speed, \( \Delta a = \) relative acceleration, \( x_{LV} \) & \( x_{FV} \) = positions of leading and following vehicles, \( D_{LV} \) = length of leading vehicle

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Statistics</th>
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<tbody>
<tr>
<td>Number of cycles</td>
<td>Mean</td>
</tr>
<tr>
<td></td>
<td>444</td>
</tr>
<tr>
<td>V (volume count per cycle)</td>
<td>13.13</td>
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<tr>
<td>MTTC (s)</td>
<td>1.25</td>
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<tr>
<td>Total rear-end conflict</td>
<td>2,915</td>
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<tr>
<td>Crash record (2015 – 19)</td>
<td>9</td>
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</tbody>
</table>
Results

Three separate Bayesian hierarchical models are estimated

\[ G(z_{ij} < z | \mu_{ij}, \phi_{ij}, \xi_{ij}) = \exp \left( - \left[ 1 + \xi_{ij} \left( \frac{z - \mu_{ij}}{\exp(\phi_{ij})} \right) \right]^{-1/\xi_{ij}} \right) \]

- A stationary model
- A model with traffic volume as a covariate to the scale parameter
- A model with traffic volume as a covariate to the location parameter
## Results

<table>
<thead>
<tr>
<th>Model</th>
<th>Parameter</th>
<th>location</th>
<th>scale</th>
<th>shape</th>
<th>DIC</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>(\mu_0)</td>
<td>(\mu_V)</td>
<td>(\sigma_0)</td>
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<tr>
<td>Stationary</td>
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<td>Model with covariate in scale</td>
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<td>-4.3589</td>
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**CRICOS No. 00213J**

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Results

Model 1: Stationary Model

Model 2: With traffic volume as a covariate in the scale parameter

Model 3: With traffic volume as a covariate in the location parameter
Results

- Tail of a GEV distribution ending after the negated MTTC = 0 indicates a positive crash risk
- Greyed Cycles have positive crash risk (and are risky cycles)
- Kolmogorov–Smirnov test to compare the equality of distributions across signal cycles
- Cycles with positive crash risk are significantly different from other cycles
Crash risk varies across the time of the day

This difference in variation is statistically significant
Conclusions

- Extreme Value Theory provides a good framework to estimate real-time crash risk from traffic conflicts.

- Non-stationary models are preferable.

- The suitability of traffic conflict indicators for other crash types needs to be rigorously tested.