Innovations in Traffic Safety and Mobility

Risk Based Traffic Safety Research

Mohsen A. Jafari
Nasim Arbabzadeh
Department of Industrial & Systems Engineering
• CAIT Focus: USDOT Strategic Areas
Questions

• Why do traffic accidents happen?
  ▪ Driver behavior?
  ▪ Road?
  ▪ Vehicle?
  ▪ Traffic flow, weather, etc.?
  ▪ Traffic signals and law enforcement?
  ▪ All of the above?

• How to mitigate traffic safety risks?
  ▪ Traditional reactive & systematic approach to safety planning and engineering
  ▪ Proactive safety measures – systemic approach
  ▪ **Near real-time situational awareness for drivers**
  ▪ Near real-time situational awareness for law enforcement
  ▪ Smart and connected cars & smart roadways
  ▪ **Self-regulating smart cars – advanced cruise control/drive by-wire**
  ▪ Near real-time and dynamic insurance pricing
• Inception 2006

• Safety/mobility resource center funded by FHWA and NJ DOT

• Development of new technologies (e.g., Plan4Safety or P4S)

• Services to NJ DOT/ FHWA/ municipalities/counties/law enforcement

• TSRC has been a major force in effectively improving traffic safety in New Jersey.
Rutgers Plan4Safety (P4S)
<table>
<thead>
<tr>
<th>Ring 5 – Presentation</th>
<th>Ring 4 – Connection to other management systems</th>
<th>Ring 3 – Applications</th>
<th>Ring 2 – Advanced Functions</th>
<th>Ring 1 – Core &amp; Basic functions</th>
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<tbody>
<tr>
<td>Engineers</td>
<td>Road pavement Management</td>
<td>Safety Analysis</td>
<td>Using historical crash data</td>
<td>Using historical crash data</td>
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<td>Planners</td>
<td>ITS management</td>
<td>Safety Planning</td>
<td>Safety Performance Function</td>
<td>Trend Line</td>
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<td>Public</td>
<td>Bridge</td>
<td>Safety Engineering</td>
<td>Crash Modification Factor (CMF)</td>
<td>Hot spot analytics with different crash types</td>
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<td>Officers</td>
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<td>Safety Evaluation</td>
<td>Scenario generation &amp; diagnosis analysis</td>
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<td>General Public</td>
<td>Traffic Control Center</td>
<td>Law enforcement</td>
<td>Cost &amp; benefit analytics</td>
<td>High Risk Road Segments</td>
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<td>Public Officials</td>
<td>Emergency Management</td>
<td>Peds and bikes</td>
<td>Advanced Filtering</td>
<td>Crash Rates</td>
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<td>Capital Planning</td>
<td>Commercial vehicles</td>
<td>Extended GIS mapping</td>
<td>Critical Crash Rate</td>
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<td>Public Transit</td>
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<td>Asset Management</td>
<td>Situational Awareness</td>
<td>Crash prediction</td>
<td>Critical Severity Rate</td>
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<td>Risk Management</td>
<td>Safety Training</td>
<td>Using near miss data</td>
<td>High Risk rural Roads</td>
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<td>Public Information Portal</td>
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<td>Using hybrid data</td>
<td>Intersection Analysis</td>
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<td>Insurance Management</td>
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<td>Crash forecasting</td>
<td>Intersection ranking</td>
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<td>Driver violation check</td>
<td>High Risk Urban Roads</td>
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<td>Safety and Mobility Analysis</td>
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<td>Post-Crash Health Economics</td>
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<td>Safety Grant Eligibility</td>
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<td>Crash Impact Simulation</td>
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<td>Crime Hot Spots</td>
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<td>Enforcement Dispatch Routing</td>
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<td>Real Time Monitoring</td>
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<td>Post evaluation</td>
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<td>Driver licensing</td>
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Plan4Safety has won many awards, including the *USDOT Best Practice Award for the 2009 National Roadway Safety Awards*,

Plan4Safety has been recognized internationally in the Annual Showcase of 2013 in the *Intertraffic World Magazine*, published in Britain,

Among the top three safety systems recognized in the USA,

P4S is in China.
Plan4Safety (P4S) is in China

- Collaboration with Anhui Keli on traffic safety and mobility started in 2012.
- A two phase project was already completed (11/2013).
- A joint program between Anhui Keli and Rutgers on ITS will start in May 2014.
- Anhui Keli is designated as one of the main ITS companies in China by the Chinese government.
Current Technology

Historical Crash data

Static Roadway Characteristics

Historical Weather data

Traditional Safety Prediction Models

- Non-individualized
- Passive

\[ \#\text{[Crashes]} = f(\text{Some Driving Features, Static Roadway Features,...}) \]

Network Screening

Crashes are Rare Events!
Safety Predictive Analytics – Historical data

Historical Database
- Crash Records
- Traffic Volume Data

Roadway (Engineering) Database:
- length of segment, lane width, shoulder width, shoulder type, roadside hazard rating, presence or absence of horizontal curve, curve characteristics, Lighting, Speed Limit and ....

Predictive Model

\[ Y_i(t) = \text{Average Crash Frequency} \]
For site \( i \) at time \( t \)

\[ Z_1 \quad Z_2 \quad \ldots \quad Z_n \]

\[ X_1(t) \quad X_2(t) \quad \ldots \quad X_k(t) \]

How to find a good model?

- Based on AADT and Roadway Length
- Models were developed by data from specific states

Adjust the calculated SPF predicted value for base conditions to actual or proposed conditions

Adjust SPF to reflect local conditions: Climate, Driver populations, Animal populations, Crash Reporting System.

Improve crash estimations by combining predicted data with historical data

Inputs

\[ N_{\text{predicted}} = SPF \times (CMF1 \times CMF2 \times \ldots) \times C \]

\[ N_{\text{expected}} = w \times N_{\text{predicted}} + (1-w) \times N_{\text{observed}} \]

Average Crash Frequency

Empirical Bayesian Method
Safety Predictive Analytics – Historical data

Poisson Model (popular model)

\[ N_i(t): \# \text{ of crashes in site } i \text{ and year } t \]

\[ f(N_i(t), \lambda_i) = e^{-\lambda_i} \frac{(\lambda_i t)^{N_i(t)}}{N_i(t)!} \]

\[ E(N_i(t)) = \exp(\sum_{j=0}^{p} \beta_j x_j) \]

Average crash at site \( i \) and year \( t \)

Roadway characteristics and traffic information

Negative binomial model

Assume that the Poisson parameter is random variable (with gamma distribution)

\[
 f(N_i | x_i, \lambda, \nu, \delta) = \int_0^\infty e^{-\lambda_i} \frac{(\lambda_i)^{N_i}}{N_i!} \cdot G(\lambda_i | \nu, \delta) \cdot d\lambda_i 
\]

\[
 f(N_i | x_i, \nu, \delta) = \frac{\Gamma(\nu + N_i)}{\Gamma(\nu) \Gamma(N_i + 1)} \left( \frac{\delta}{1 + \delta} \right)^\nu \left( \frac{1}{1 + \delta} \right)^{N_i} 
\]

\[
 f(N_i | x_i, \alpha, \delta) = \frac{\Gamma(N_i + 1/\alpha)}{\Gamma(1/\alpha) \Gamma(N_i + 1)} \left( \frac{1}{1 + \alpha \mu_i} \right)^{1/\alpha} \left( 1 - \frac{1}{1 + \alpha \mu_i} \right)^{N_i} 
\]

\[ E(N_i) = \mu_i = \exp(\sum_{j=0}^{p} \beta_j x_j) \]
Input features and response variables used for building the proposed crash prediction model:

<table>
<thead>
<tr>
<th>Input Features</th>
<th>Feature</th>
<th>Data Type</th>
<th>Base Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_1 )</td>
<td>Road Segment ID</td>
<td>Number</td>
<td>-</td>
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<tr>
<td>( x_2 )</td>
<td>SRI</td>
<td>Text</td>
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<tr>
<td>( x_3 )</td>
<td>Location Type</td>
<td>Categorical</td>
<td>-</td>
</tr>
<tr>
<td>( x_4 )</td>
<td>Facility type</td>
<td>Categorical</td>
<td>-</td>
</tr>
<tr>
<td>( x_5 )</td>
<td>Road Segment Length</td>
<td>Real</td>
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</tr>
<tr>
<td>( x_6 )</td>
<td>Start-Point</td>
<td>Real</td>
<td>-</td>
</tr>
<tr>
<td>( x_7 )</td>
<td>End-Point</td>
<td>Real</td>
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<tr>
<td>( x_8 )</td>
<td>Number of Lane</td>
<td>Integer</td>
<td>-</td>
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<tr>
<td>( x_9 )</td>
<td>Road Total Width</td>
<td>Real</td>
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<tr>
<td>( x_{10} )</td>
<td>Speed Limit</td>
<td>Integer</td>
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<td>( x_{11} )</td>
<td>AADT</td>
<td>Real</td>
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<tr>
<td>( x_{12} )</td>
<td>Lane Width</td>
<td>Real</td>
<td>3.75m</td>
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<tr>
<td>( x_{13} )</td>
<td>Shoulder Width</td>
<td>Real</td>
<td>2.5m</td>
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<tr>
<td>( x_{14} )</td>
<td>Shoulder Type</td>
<td>Categorical</td>
<td>Paved</td>
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<tr>
<td>( x_{15} )</td>
<td>Presence of Median</td>
<td>Binary</td>
<td>absence of a lane</td>
</tr>
<tr>
<td>( x_{16} )</td>
<td>Median Width</td>
<td>Real</td>
<td>4.5m urban, 9.0m Rural</td>
</tr>
<tr>
<td>( x_{17} )</td>
<td>Median Barrier</td>
<td>Binary</td>
<td>absence of a lane</td>
</tr>
<tr>
<td>( x_{18} )</td>
<td>Passing lane</td>
<td>Number</td>
<td>absence of a lane</td>
</tr>
<tr>
<td>( x_{19} )</td>
<td>2-way left-turn</td>
<td>Binary</td>
<td>absence of 2-way left-turn</td>
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<tr>
<td>( x_{20} )</td>
<td>Lighting</td>
<td>Binary</td>
<td>absence of Lighting</td>
</tr>
<tr>
<td>( x_{21} )</td>
<td>Presence of on-street parking</td>
<td>Binary</td>
<td>absence of on-street parking</td>
</tr>
<tr>
<td>( x_{22} )</td>
<td>Type of on-street parking</td>
<td>Binary</td>
<td>absence of on-street parking</td>
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</table>

<table>
<thead>
<tr>
<th>Response Variables</th>
<th>Feature</th>
<th>Data Type</th>
<th>Base Condition</th>
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</thead>
<tbody>
<tr>
<td>( Y )</td>
<td>Total Crashes</td>
<td>Integer</td>
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</tr>
<tr>
<td>( Y_1 )</td>
<td>Fatal Crashes</td>
<td>Integer</td>
<td>-</td>
</tr>
<tr>
<td>( Y_2 )</td>
<td>Major Injuries Crashes</td>
<td>Integer</td>
<td>-</td>
</tr>
<tr>
<td>( Y_3 )</td>
<td>Minor Injuries Crashes</td>
<td>Integer</td>
<td>-</td>
</tr>
<tr>
<td>( Y_4 )</td>
<td>Property-Only-Damage</td>
<td>Integer</td>
<td>-</td>
</tr>
</tbody>
</table>

Comparision of Real and Predicted Crashes for the same year.
Evolution of Traffic Safety Prediction Models

Historical Crash data

Static Roadway Characteristics

Crowdsourcing

V2V, V2I

Network Screening

Weather data

NDD

Traditional Safety Prediction Models
• Non-individualized
• Passive

\[ \#\{\text{Crashes}\} = f(\text{Some Driving Features, Static Roadway Features, \ldots}) \]

Advanced Technologies => New Data Streams

Real-time Safety Prediction Model
• Individualized
• Active

\[ \text{Pr}\{\text{Crash, Near-Crash, Baseline}\} = f(\text{Historical Crashes, Real-time Roadway, \& Drivers Features, Incidents, \ldots}) \]

Crashes are Rare Events!
Smart and connected vehicle technology

These new safety technologies are very helpful but they miss the interrelationship among multiple causes of risky situations!
Multiple Data Streams

Static Data
Roadway conditions, traffic signals, etc.

Dynamic data

Weather & roadway conditions real time
Weather data and roadway condition can be reported near real time by sensors, vehicles, and roadway sensors.

Near miss, IOT & roadway sensors
Crashes are rare events and crash based safety solutions are reactive; Near real time near miss data and unsafe driving conditions can protect vulnerable users, e.g., pedestrians and bicycles.

Traffic flow data V2V,V2I & crowdsourcing
Warnings & real time unsafe driving conditions generated between vehicles and between vehicles and infrastructure;

Naturalistic Driving Data
Illustration of Traffic Safety Risk Factors

Internal:
- Vehicle and Driver data
- Immediate past & present Vehicle and Driver data ($X_V, X_D$)

External:
- Road Incidents
- Roadway characteristics

Predicted driving outcome ($Y$) at time $t+1$

At sample time $t$:
- Internal variables: $X_V, X_D, X_T$
- External variables: $X_R, X_S, X_I, X_W$

Target Vehicle & Driver

Time, $X_T$

Weather, $X_W$
Real-Time Risk Based Safety Model

In-vehicle data
- In-vehicle’s sensors, radars, cameras, OBD devices, GPS
- Naturalistic driving database
- Vehicle and driver data

External data
- Driver surveys
- V2V, V2I
- Social Media (crowd-sourced data)
- Real-time traffic flow and incidents database
- Weather data
- Weather database
- Environment data

Engineering data
- Environment data
- SLD, ESRI, State inventory, Asset health condition
- Roadway characteristics database

Historical crash data
- Police reports
- Historical crashes
- Network screening index

Prediction model

Users
- Drivers
- Network owners
- Insurance companies
Classification model’s input/output

State Vector at time t:

\[ X^n = [\text{Driver, Vehicle, Road, Weather, Time, Network-Screening Factor}] \]

- **Internal factors**
- **External factors**

Network-Screening Factor

Real-Time Risk-Based Safety Model

Crash risk

Real Time Alert System

- No crash
- Near crash
- Crash
Near Real-Time Risk Based Safety Model (cont.)

Application Illustration

- **State:** $S_0, S_1, S_2, \ldots, S_{k-1}, S_k, S_{k+1}, \ldots, S_n$
- **Risk:** Colors indicate varying levels of risk
- **Time:** 30 sec intervals

- **Origin**
- **Destination**
Overall Framework

Data Fused Risk Model

Data Layer
- Naturalistic driving data
- Weather data
- Roadway data
- Traffic flow data
- Historical crash data

Data resources
- Naturalistic driving database
  - Driver distraction
  - Driver Behavior
  - Demographics
  - Speed
  - Acceleration
- Weather data
- SLD database
  - Type of road
  - Through lanes
  - Inside/outside shoulders
  - Median type
  - Surface description
- Traffic flow data
  - Accident ahead
  - Dangerous intersection
  - Work zone
  - Speed camera
  - Dangerous curves
- Historical crash database

Tools
- Simulation
- Regression models
- Classification models
- Multivariate Time Series model

Risk function
Real-time Risk Based Safety Prediction Model