Building Cross-Validated Injury Risk Functions for Car-to-Car Impacts from Pre-Crash Predictors Only

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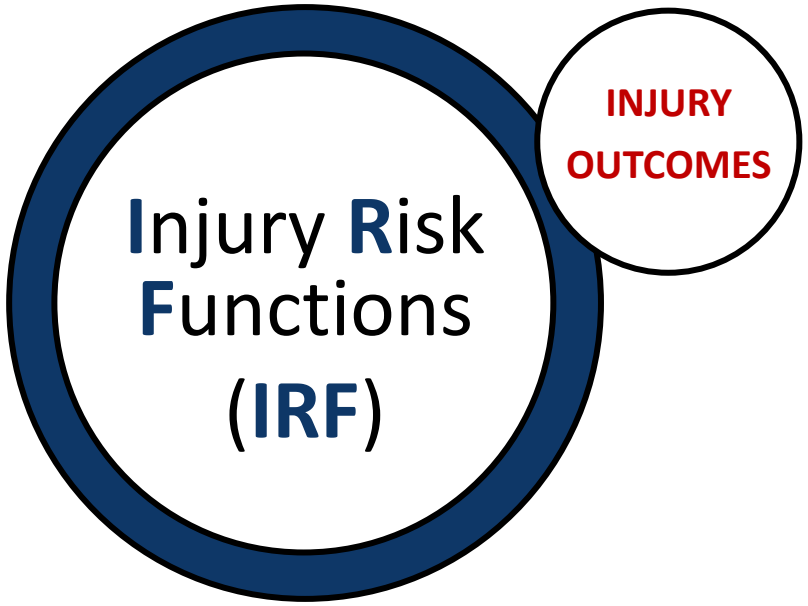
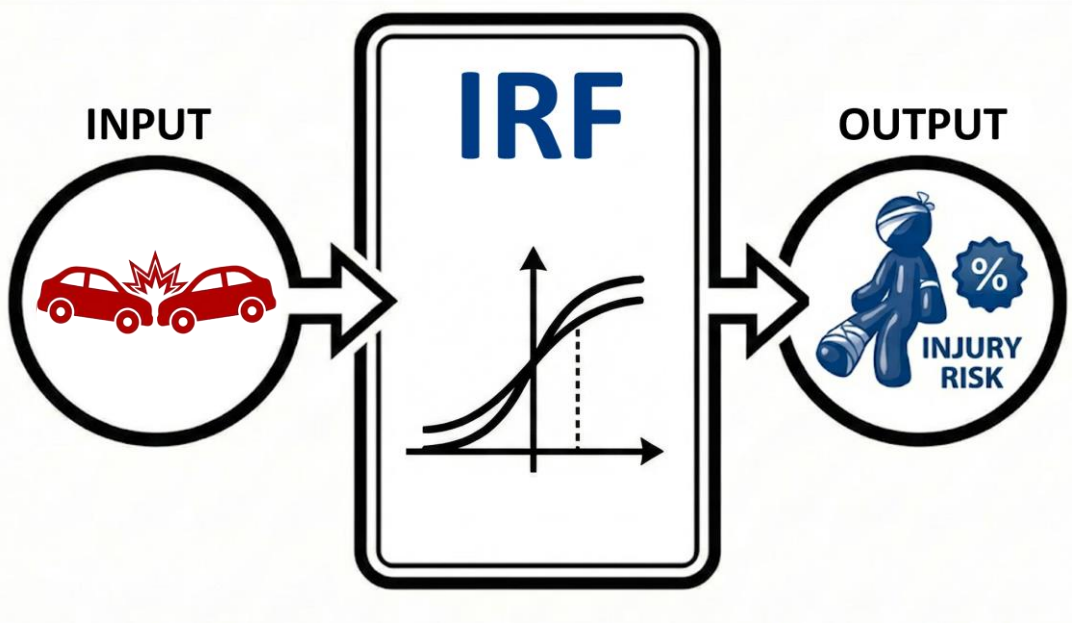
Introduction





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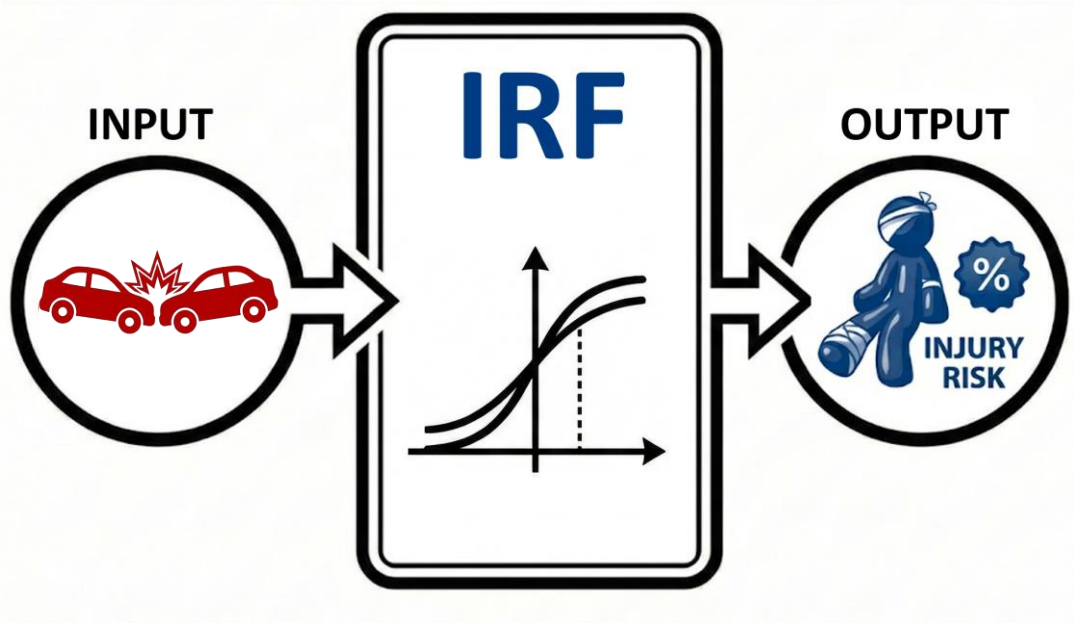

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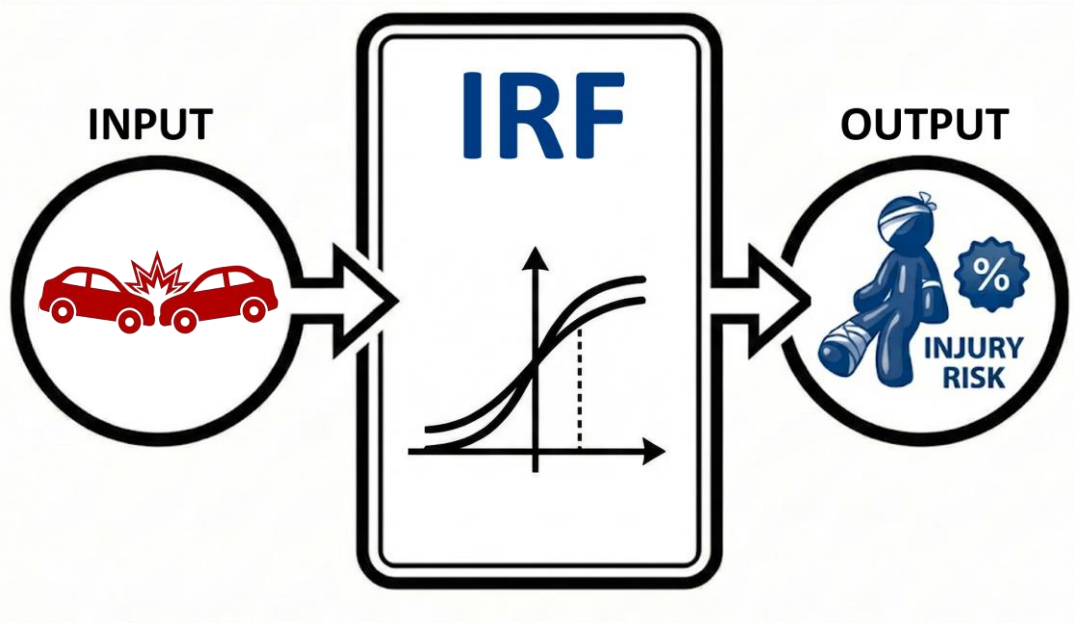

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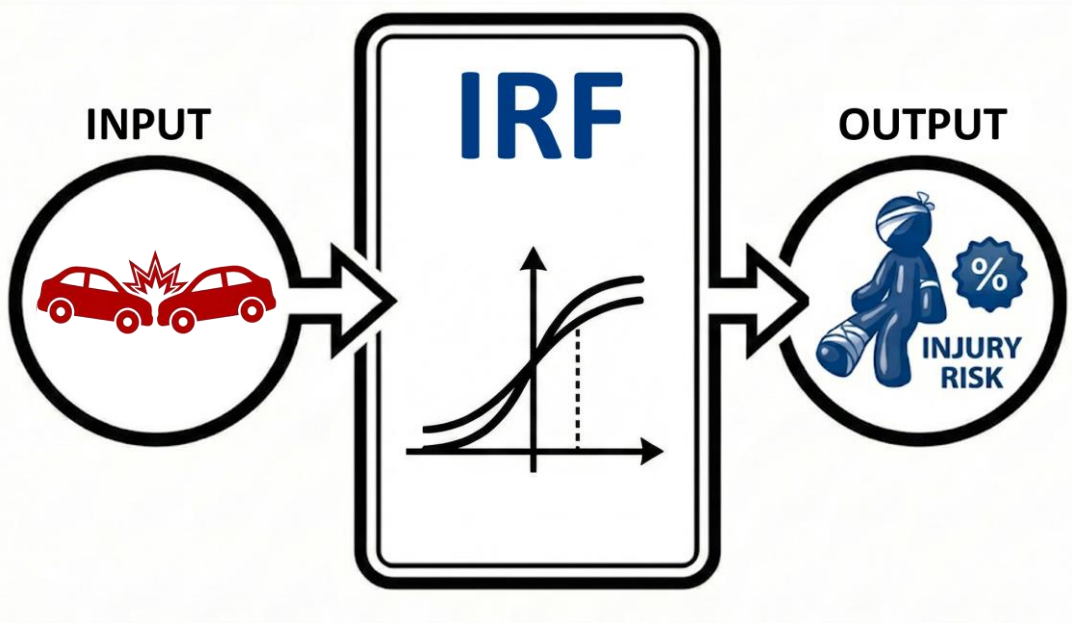

The Challenge of IRF Heterogeneity

SOME IRF ISSUES...

1. **Geographical & Coding Constraints**
   - Standardization Issues
   - Local Validity

2.

3.

4.

The Challenge of IRF Heterogeneity

Context
Approach
Modeling
Validation
Further Steps

SOME IRF ISSUES...

1. **Geographical & Coding Constraints**
   - Standardization Issues
   - Local Validity

2. **Predictor Inconsistency**
   - Diverse Inputs
     - Velocity-based?
     - Energy-based?

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3. **Dataset Imbalance**
   - Severity Skew

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SOME IRF ISSUES...

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   - Diverse Inputs
     - Velocity-based?
     - Energy-based?

3. **Dataset Imbalance**
   - Severity Skew

4. **Methodological Sensitivity**
   - Model Variety
   - Algorithm Dependency

Research Objectives

Development of a novel methodological framework that ensures:

1. Geographical Independence → Cross-validation on geographically different datasets

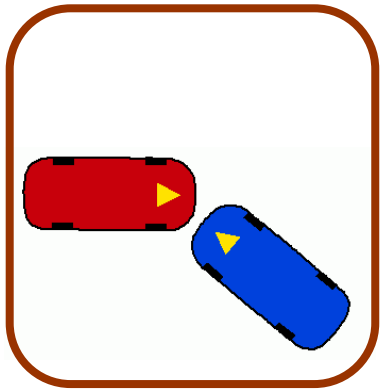
2. Predictor Objectivization → Model-agnostic feature selection

To obtain new car-to-car IRFs based on:

3. Pre-Crash Predictors Only

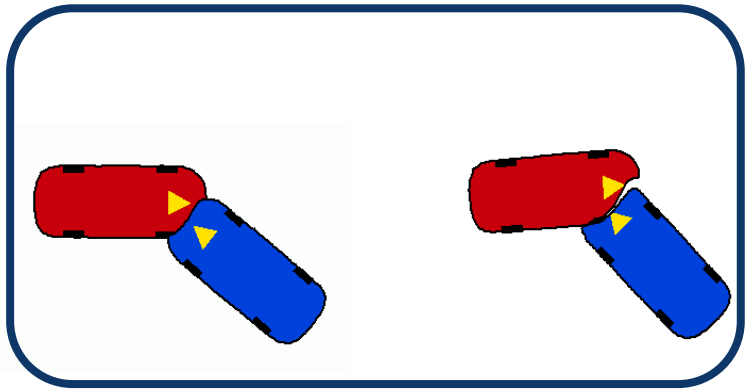
Pre-Crash Predictors

PRE-CRASH PHASE



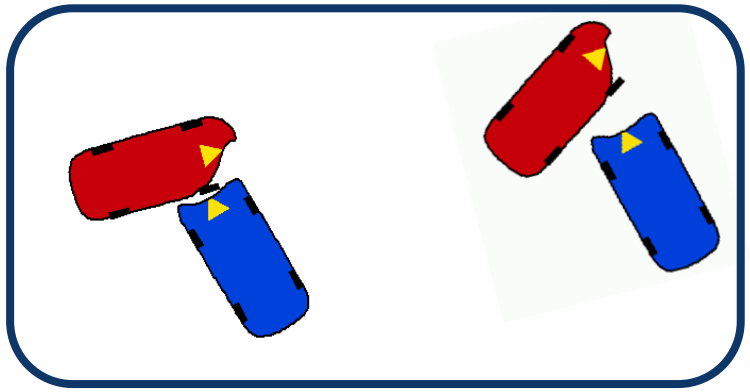
- Vehicle mass
- Wheelbase
- Closing speed
- Impacted area
- Stiffnesses
- [...]

CRASH PHASE



- Post-collision speed
- ΔV
- Deformation energy
- EES
- [...]

POST-CRASH PHASE



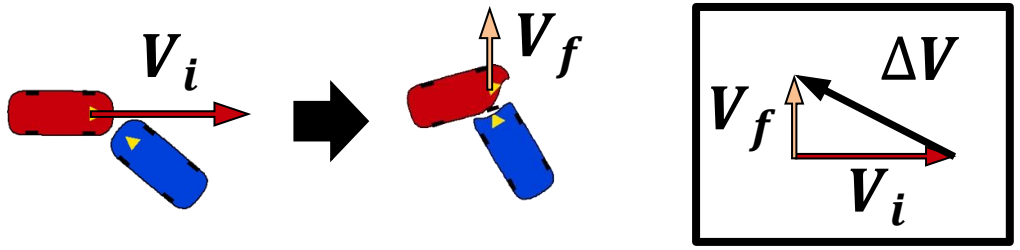
- Resting positions
- Residual deformations

Several car-to-car IRFs rely on ΔV or EES

Pre-Crash Predictors

ΔV

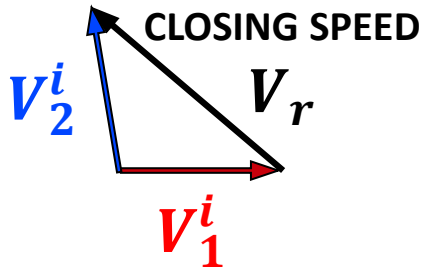
The total change in a vehicle's velocity during a collision event.



From CRASH
To PRE-CRASH
Predictors

$$\Delta V = V_r \cdot CMI$$ *(retrospective formulation)*

CRASH MOMENTUM INDEX



$$CMI = \frac{\gamma_1 \gamma_2 (1 + \varepsilon_i)}{(\gamma_2 + \gamma_1 R_m)}$$

(prospective formulation)

$$\gamma_i = \frac{k_i^2}{k_i^2 + h_i^2}$$

- V_r closing speed
- k radius of gyration
- h arm of the force
- ε restitution coefficient
- R_m mass ratio

Pre-Crash Predictors

Context
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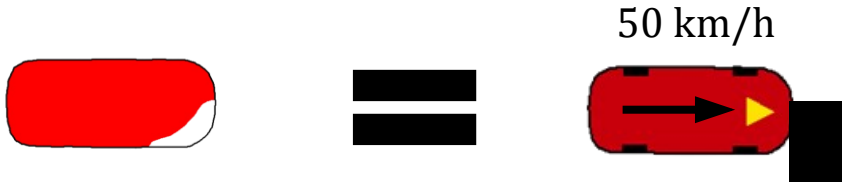
EES

The speed against a rigid barrier required to produce the observed damage.

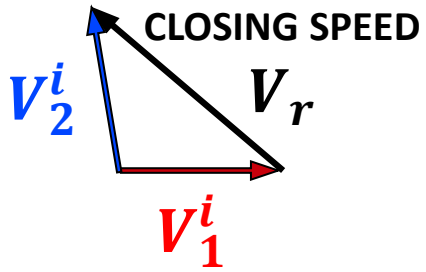


From CRASH
To PRE-CRASH
Predictors

$$EES = V_r \cdot CSI$$

(retrospective formulation)

CRASH SEVERITY INDEX



$$CSI = \sqrt{\frac{\gamma_1\gamma_2(1-\varepsilon_i^2)}{(1+R_k)(\gamma_2+\gamma_1 R_m)}}$$

(prospective formulation)

$$\gamma_i = \frac{k_i^2}{k_i^2 + h_i^2}$$

- V_r closing speed
- k radius of gyration
- h arm of the force
- ε restitution coefficient
- R_m mass ratio
- R_k stiffness ratio

Why Use Only Pre-Crash Predictors?

To maximize IRF applicability across varying levels of data completeness!

CASE	DATABASE STATUS	ΔV Availability	EES Availability	Geometric and pre-crash data
1	**Incomplete** (No Velocity-based parameters)	✗	✓	✓
2	**Incomplete** (No Energy-based parameters)	✓	✗	✓
3	**Minimal** (Geometric & pre-crash data only)	✗	✗	✓
4	**Exhaustive**	✓	✓	✓

CMI *(prospective)* $CMI = \frac{\gamma_1\gamma_2(1+\varepsilon_i)}{(\gamma_2+\gamma_1 R_m)}$
CSI *(retrospective)* $CSI = EES/V_r$

CMI *(retrospective)* $CMI = \Delta V/V_r$
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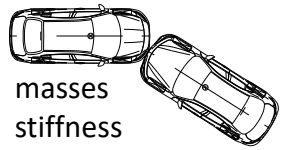
CMI *(prospective)*
CSI *(prospective)*



CMI *(retrospective)* $CMI = \Delta V/V_r$
CSI *(retrospective)* $CSI = EES/V_r$

The IRF Modeling Pipeline

- Context
- Approach
- Modeling
- Validation
- Further Steps

DATASET

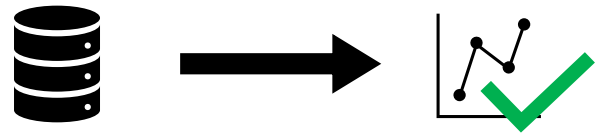
1 **DATA PREPARATION**
- Data Filtering & Consistency Check
- Predictor Normalization

2

3

4

IRF



DATASET

Modeling...

IRF

(Injury Risk Function)

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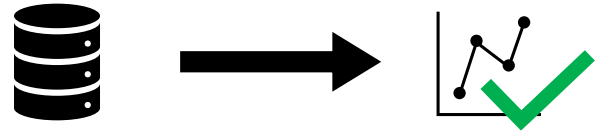

2. **PREDICTOR SELECTION**
   - Model-Agnostic Feature Ranking → **ReliefF** algorithm
   - Parsimonious Predictor Selection → Greedy **Stepwise-BIC** selection

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IRF

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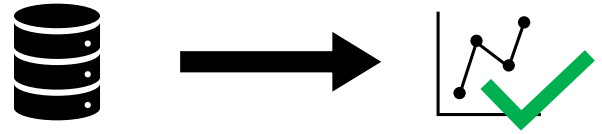

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- Model-Agnostic Feature Ranking → **ReliefF** algorithm
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3 **MODEL BUILDING**
- Target Variable Definition *(MAIS+)* → **M**aximum **A**bbreviated **I**njury **S**cale **+**
- Link Function Benchmarking → **Logit**, **Probit** or **Comp-loglog**

4

IRF

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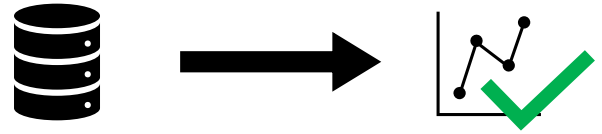

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4 **VALIDATION STRATEGY**
- Internal Assessment *(Goodness-of-Fit)* → Based on **A**rea **U**nder the **C**urve metric
- External Validation *(Generalization)*

HOW?

IRF

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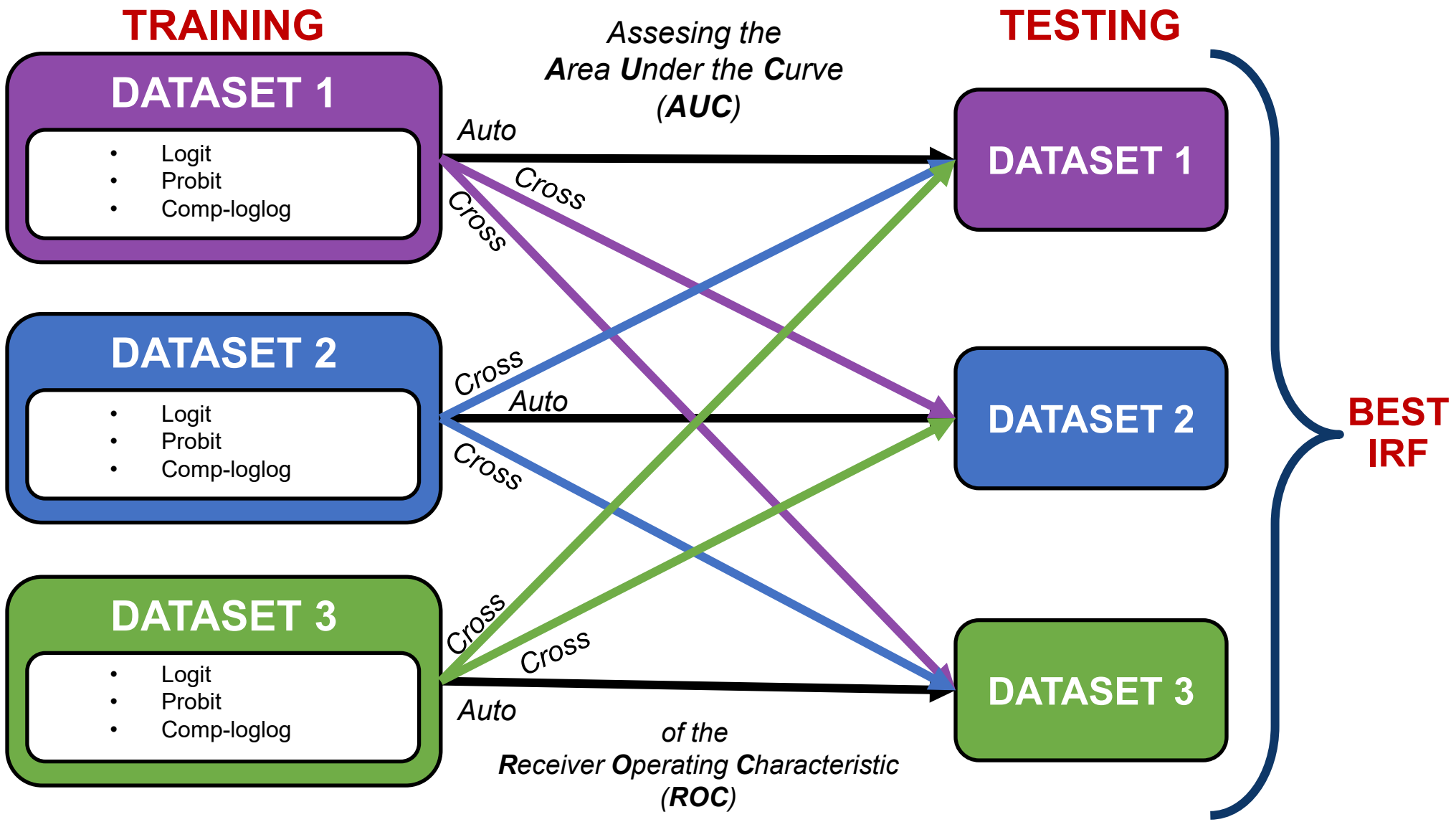
Cross-Dataset Validation



Example: Severe Injuries (MAIS 3+)

- Context
- Approach
- Modeling
- Validation
- Further Steps

Databases

Worldwide IGLAD

U.S.A. NHTSA

France VOIESUR

$$Score = \frac{max\ (AUC_i) + min\ (AUC_i)}{2}$$

TRAINING	TESTING	SEVERE INJURIES (MAIS 3+)		
		LOGIT	PROBIT	CLOGLOG
VOIESUR	**VOIESUR**	0.9503	0.9473	0.9471
	NHTSA/NASS	0.8005	0.8104	0.8101
	IGLAD	0.7217	0.7422	0.7420
	Score	**0.836**	**0.845**	**0.845**
NHTSA NASS CDS	VOIESUR	0.8336	0.8315	0.8304
	NHTSA/NASS	0.8750	0.8757	0.8719
	IGLAD	0.8174	0.8217	0.8171
	Score	**0.846**	**0.849**	**0.845**
IGLAD	VOIESUR	0.8138	0.8079	0.7997
	NHTSA/NASS	0.8544	0.8557	0.8555
	IGLAD	0.8297	0.8293	0.8340
	Score	**0.834**	**0.832**	**0.828**

Highest score

Example: Severe Injuries (MAIS 3+)

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$$IR^{MAIS3+} = \Phi(\eta)$$

Φ is the **cumulative distribution function (CDF)** of the **standard normal distribution**.

$$\eta = \beta_0 + \beta_1 + \frac{x_1 - \mu_1}{\sigma_1} + \beta_2 + \frac{x_2 - \mu_2}{\sigma_2} + \beta_3 + \frac{x_3 - \mu_3}{\sigma_3}$$

Parameters:
β_0 Intercept
$\beta_{1,2,3}$ Model Coefficients
μ *Mean (Normalization)*
σ *Standard Deviation (Normalization)*

Link Function: **PROBIT**

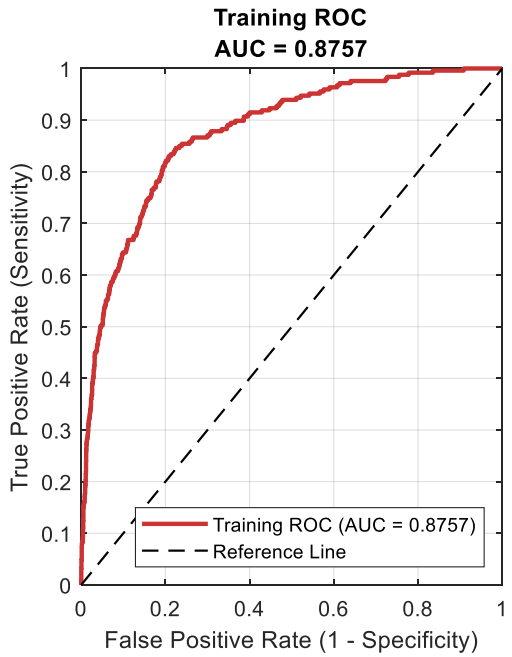
Training dataset:
NHTSA/NASS/CDS

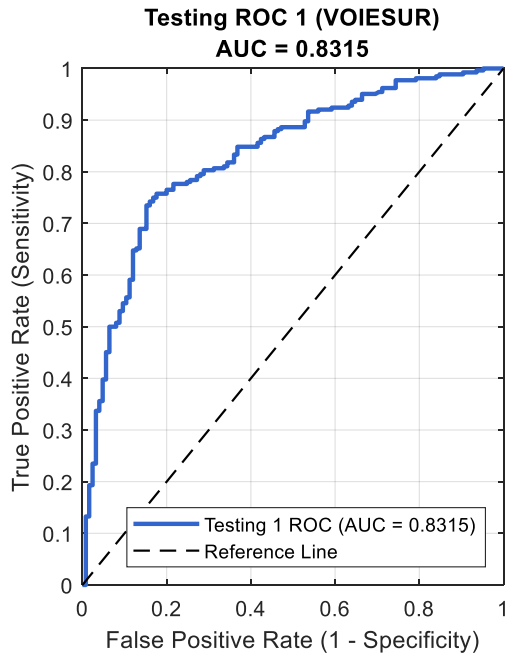
Databases

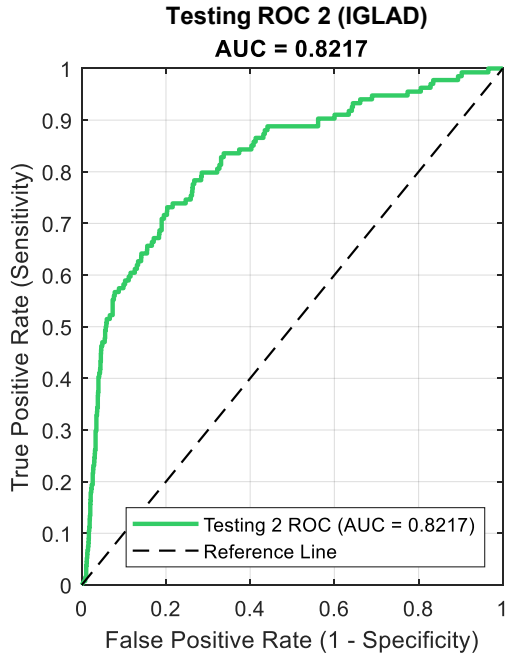
- *Worldwide* **IGLAD**
- *U.S.A.* **NHTSA** ← (used)
- *France* **VOIESUR**

Predictors (INPUT):

- $x_1 \equiv$ **CLOSING SPEED**
- $x_2 \equiv$ **CMI** (Ego Vehicle)
- $x_3 \equiv$ **CSI** (Ego Vehicle)



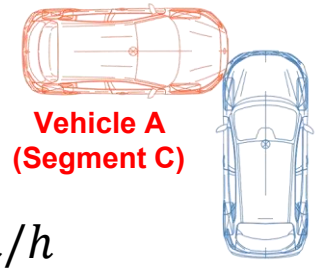




Case Study from IGLAD-PCM Dataset

FROM IGLAD DATABASE...

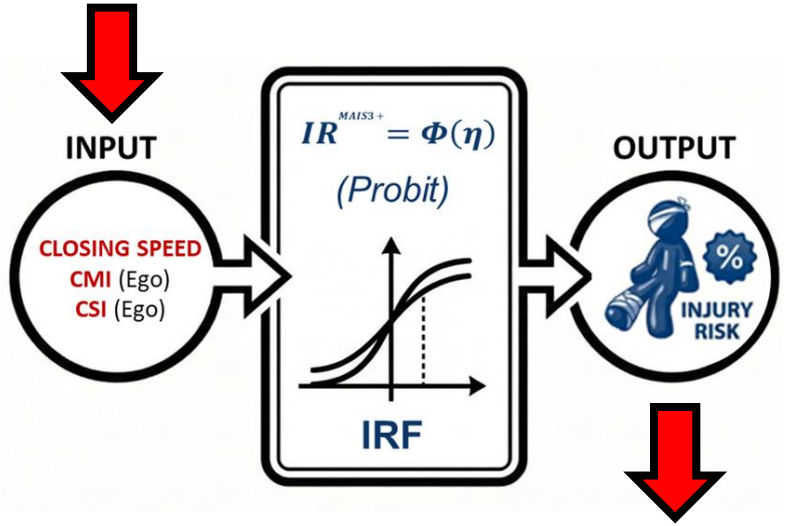
Geometric data (sketches)
Vehicle data



$V_A = 47\ km/h$ $V_B = 70\ km/h$
$\Delta V_A = 33\ km/h$ $\Delta V_B = 29\ km/h$

COMPUTING...

- **Closing speed** *(from velocities)*
- **CMI – retrospective** *(ΔV and Closing speed)*
- **CSI – prospective** (sketches, masses, stiffnesses)



CAR **OCCUPANTS**	MAIS 3+ **INJURY RISK**
A – Segment C	**9 %**
B – Segment C-SUV	**4 %**

Conclusion

Development of a novel methodological framework that ensures:

1. Geographical Independence
2. Predictor Objectivization

To obtain new car-to-car IRFs based on:

3. Pre-Crash Predictors Only

Further Steps

Safety Protocols for Regulation & Consumer

PASSIVE SAFETY

Informing new or updated **crash test protocols** by identifying the most **critical pre-crash scenarios** from real-world data.

ACTIVE SAFETY

Enabling **IR estimation in ADAS tests against inflatable targets** (balloons). Due to their lack of structural stiffness, crash accelerations are not recorded, and standard metrics like **ΔV and EES cannot be calculated**.

Insurtech

Transitioning to **dynamic risk profiling based on real-time exposure** rather than crash history.

Autonomous Driving

On-board IR computation to optimize **autonomous evasive maneuvers in real-time** during emergencies.

THANK YOU!

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