IVORY – AI for Vision Zero in Road Safety

From Infrastructure to Behaviour: Learning Risk Patterns from Telematics

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Presentation Overview

- Introduction: telematics data as SMoS
- Our lines of work
  - Harsh-event from telematics data as a **measurable safety output** and its relationship with environment attributes
    - Computer Vision
    - Regression models
  - Driving behavior from telematics data used as an input to understand **hazardous patterns throughout the road network**
    - Graph Neural Network
    - Clustering

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Telematics Data as SMoS

- Because of the **restrictions of crash data, Surrogate Measures of Safety – SMoS** have been increasingly used as a safety measure
- As an SMoS, telematics data can give insights about road user behaviour by measuring harsh event **frequency** and **intensity**
- Those events can be further associated with:
  - **Environment features**
  - **Traffic conditions**
  - **Weather**
  - **Time**

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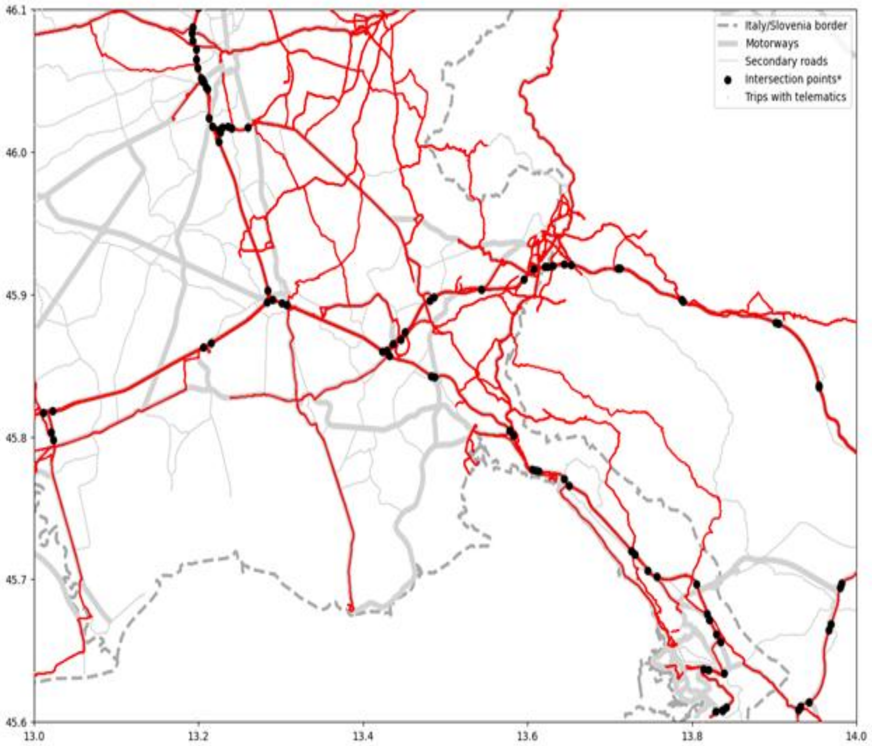
Harsh Events and Visual Environment Attributes

- **Goal**:
  - explore whether street view image attributes can be used to estimate risk level based on telematics data
- **Data**:
  - Motorway junctions close to Gorizia, Italy
  - Telematics data: harsh events (braking and acceleration) from 322 trips between March/2021 and March/2025 from OSeven
  - Imagery data: Mapillary and DeepLabV3+ segmentation with Cityscapes training
  - Selection criteria: 50-m circular buffer and at least 2 trips
- **Methods**:
  - Spearman Correlation
  - Count models: Poisson and Negative Binomial



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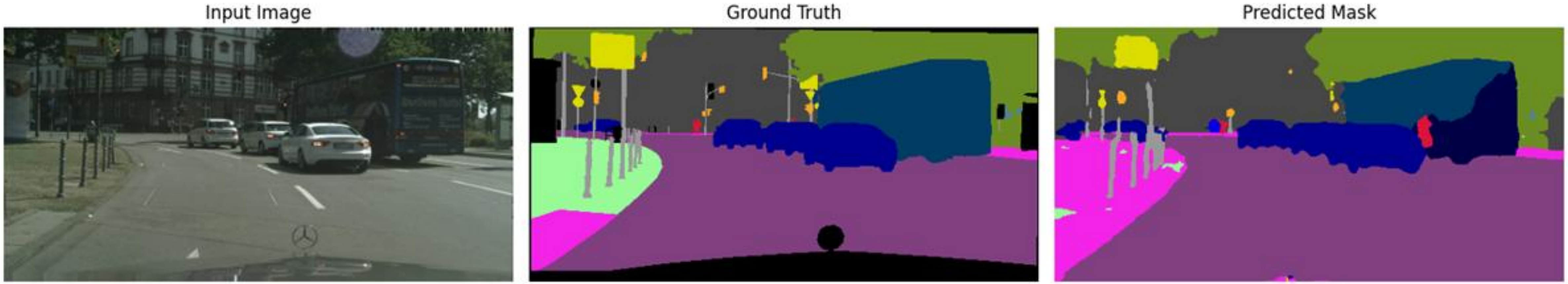
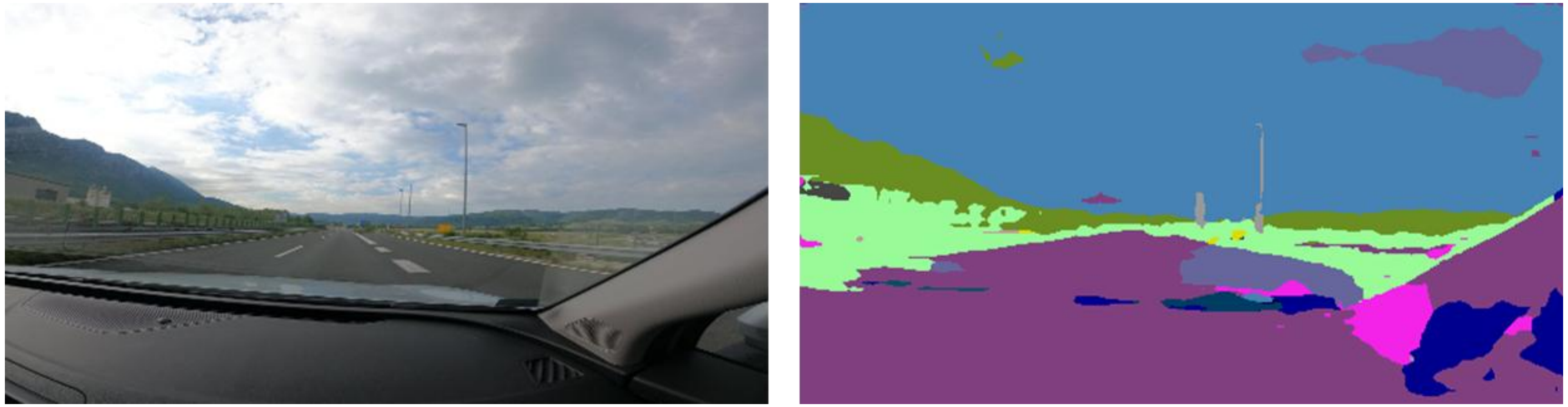
Visual Environment Attributes from Cityscapes





- 18 attributes: road, sidewalk, building, wall, fence, pole, traffic light, traffic sign, vegetation, terrain, sky, person, rider, car, truck, bus, train, motorcycle, bicycle

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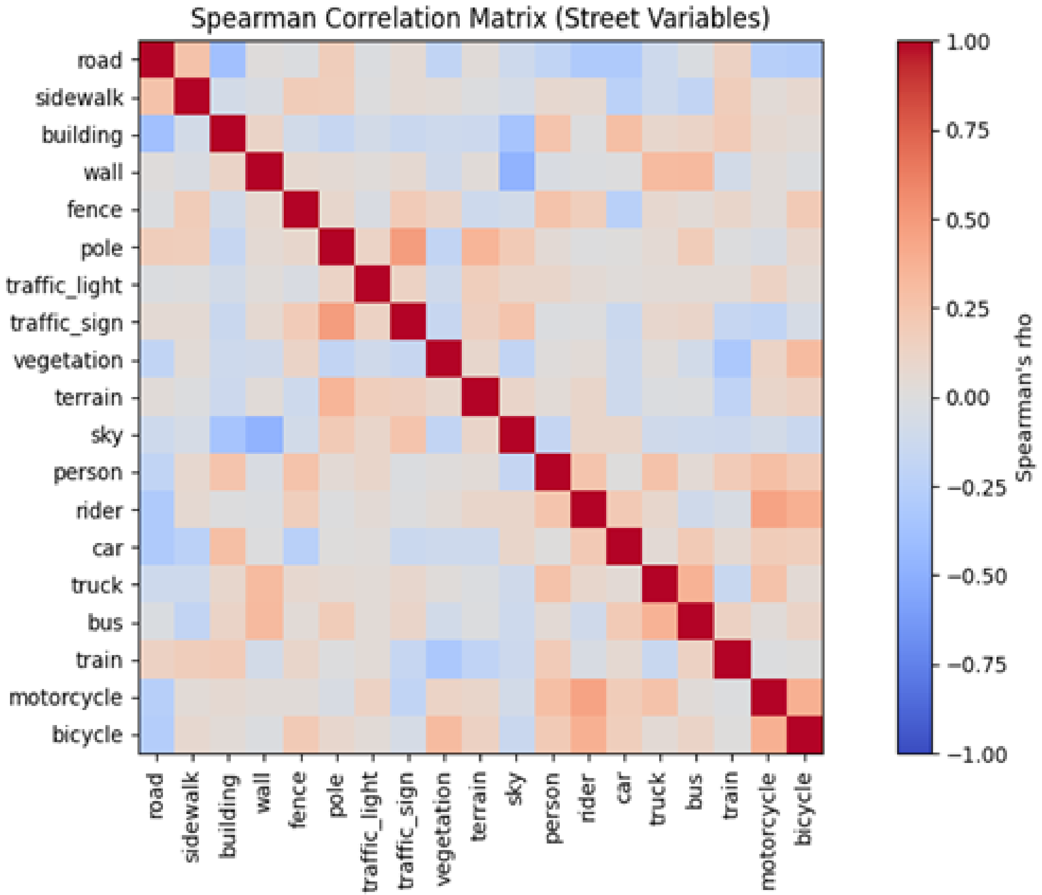
Correlation Results

- Autocorrelation between some street variables:
  - Wall and Sky: negative correlation
  - Rider and motorcycle/bike: positive correlation
- Only terrain presented significant correlation with number of harsh events
  - ρ = -0.2339
  - p-value = 0.0204



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Regression Results

- **Poisson** had a better fit than Negative Binomial
- Including **number of trips as a variable** instead of an offset increased model prediction, as well as adding **speed**
- **Flat** pixels consistently showed high statistical significance, suggesting that narrower roads and broad view distance improve behaviour generally
- Road users, poles and signs might be better related with number **count** than pixel proportion

Model	Number trips as offset		Number of trips and speed as variables	
Variables	β	p-value	β	p-value
Constant	-7.3278	0.000	-1.8787	0.199
Construction	0.3165	0.049	0.2894	0.168
Flat	-0.2593	0.000	-0.1549	0.010
Poles and signs	-0.0598	0.475	-0.1098	0.217
Nature	0.6816	0.117	1.1323	0.027
Road users	-0.4889	0.005	-0.2778	0.156
Number of Trips			0.0222	0.000
Mean speed			-0.0294	0.003
Pseudo-R^2	0.3730		0.5431	
AICc	112.7693		105.0355	

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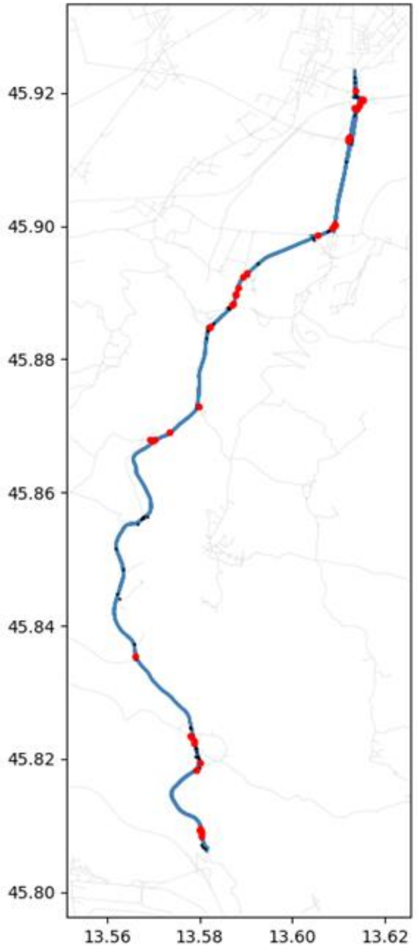
Current and Future Work

- Using **iRAP** coded attributes for harsh event prediction
- Using different **models** to obtain relevant road information from **imagery data** for a completely **automated** pipeline
- Challenges: working with a dataset that is simultaneously **imbalanced** and **small**



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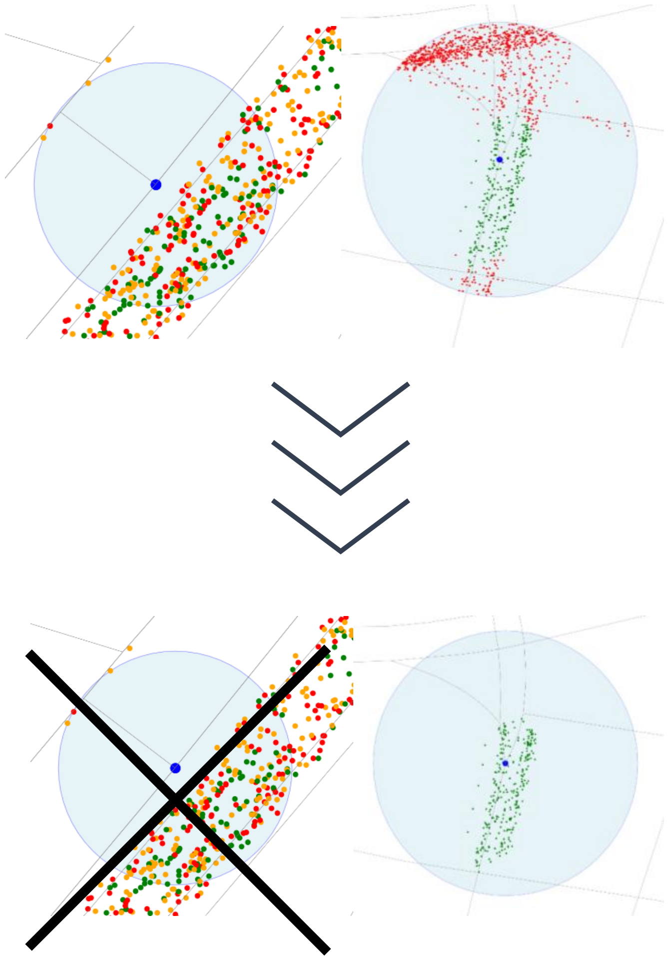
Telematics Data Integration with Road Network

- **Goal**: Spatial analysis of driving behavior using per-second telematics.
- **Integration Approach**:
  - **Edges**: Assign each observation to the closest road segment, then aggregate (average, sum, etc.).
  - **Nodes:**
    - **Basic**: Use simple buffers around intersections.
    - **Improved:** Only include observations on edges directly connected to the node within the buffer area.



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Introduction to Graph Neural Network

What are GNNs?

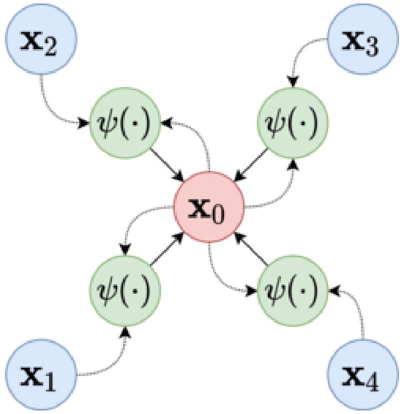
- Neural networks designed to work on graph-structured data (nodes + edges).
- Capture relationships and interactions between entities, not just independent features.

Why use GNNs?

- Standard neural networks (CNNs, MLPs) assume grid-like or independent data.
- GNNs model dependencies, making them ideal for social networks, traffic, telematics, and molecular data.

Key Idea

- Each node updates its representation by aggregating features from neighbors.
- Enables learning both local structure and global patterns.



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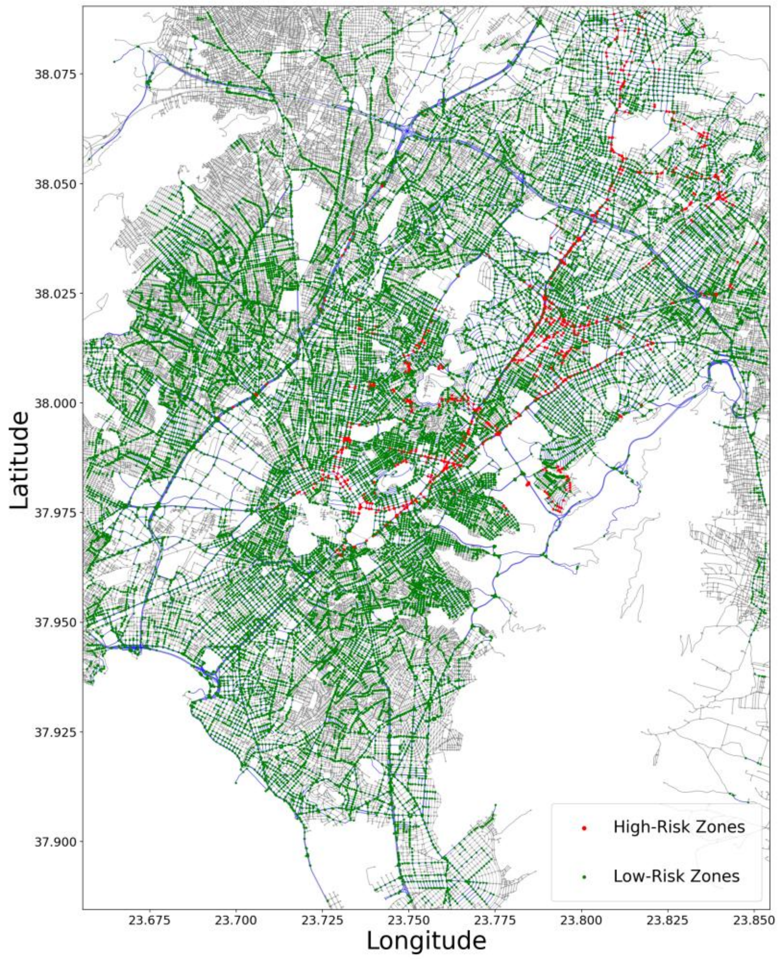
Graph Neural Networks Meet Cluster Analysis

- **GNNs on Road Networks**
  - Spatially aggregated telematics → node embeddings capturing network structure + driving behavior.
- **Node Embeddings → Clustering**
  - Learned node representations are fed into clustering algorithms.
- **Benefits**:
  - More reliable clustering vs raw features.
  - Improved interpretability of driving patterns.
- **Driver Behavior Groups**
  - Calm zones: 🟢 nodes → smooth driving.
  - Unsafe zones: 🔴 nodes → aggressive or careless driving.



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Graph Neural Networks Meet Cluster Analysis

Loss Function Tweak

- Encourage each node to be similar to itself under small perturbations (**positive pair**) and distinct from other sampled nodes (**negative pairs**).
- From global negative sampling → local negative sampling.

- Focuses on more meaningful node contrasts improving the clustering performance.

Temporal Dimension

- Weekly aggregation captures temporal patterns.

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Towards a Multiscale Framework

- **Multiscale in spatial processes**
  - **Scale Matters**: Different locations need different context.
  - **Key Idea**: All locations use the same data and features, but each adapts to its local spatial context.
- **Geographical Weighted Attention Mechanism** in GAT

$$h_i{}' = \sum_{j\in\mathcal{N}(i)} \left(\frac{e^{LeakyReLU\left(a_1{}^T W h_i + a_2{}^T W h_j\right) - \frac{d_{ij}{}^2}{2h^2}}}{\sum_{k\in\mathcal{N}(i)} e^{LeakyReLU(a_1{}^T W h_i + a_2{}^T W h_k) - \frac{d_{ik}{}^2}{2h^2}}} \right) h_j$$

- **Propagation**: GAT layer updates features with distance-weighted attention.
  - $\frac{d_{ij}{}^2}{2h^2}$ is the modulator of the routing strength layer by layer.
  - The attention for each neighbor j is **weighted both by feature similarity** (standard GAT) **and by spatial proximity**.

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Key Findings and Future Directions

- **Network-Aware Driver Behavior Insights**
  - Node embeddings + clustering → better interpretability of driver behavior patterns.
- **Time Dimension**
  - Temporal patterns captured through aggregation over time.
- **Improved Clustering via Loss Function Tweaks**
  - Local negative sampling emphasizes meaningful contrasts, resulting in more robust and insightful clustering.
- **Future Work**
  - Extend the approach to a multiscale architecture that adapts to local spatial contexts, capturing complex dynamics more effectively.

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Thank you!

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