

VEHITS 2026, Benidorm, Spain – May 18th, 2026

The Use of Contextual Reasoning for Road Users' Behaviour Prediction in the Framework of Automated Driving Technologies



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Can context-based prediction of behavior improve the socially-compliant performance of automated vehicles, accelerate their societal adoption, and extend their ODD?

ODD Detection Integrity

Why It's Hard to Detect ODD Boundaries

- Incomplete detection of critical attributes (e.g., heavy rain, fog)
- Limited forward detection range (few hundred meters)
- Edge cases (e.g., roadworks, graffiti)



Sensor and Information Limitations

- Off-board data and inference for some conditions
- ODD forecasting must include time buffer



Environmental Condition Detection Challenges

- Ambiguous thresholds (e.g., light vs. moderate rain)
- Urban context recognition varies by country



Prediction Systems and AVs

POTENTIAL BENEFITS



Safety and Efficiency



Comfort



Feeling of respect and being understood by AVs

Potential to increase the social acceptance of AVs and to accelerate their adoption

Prediction of vehicle lane change and pedestrian crossing intentions





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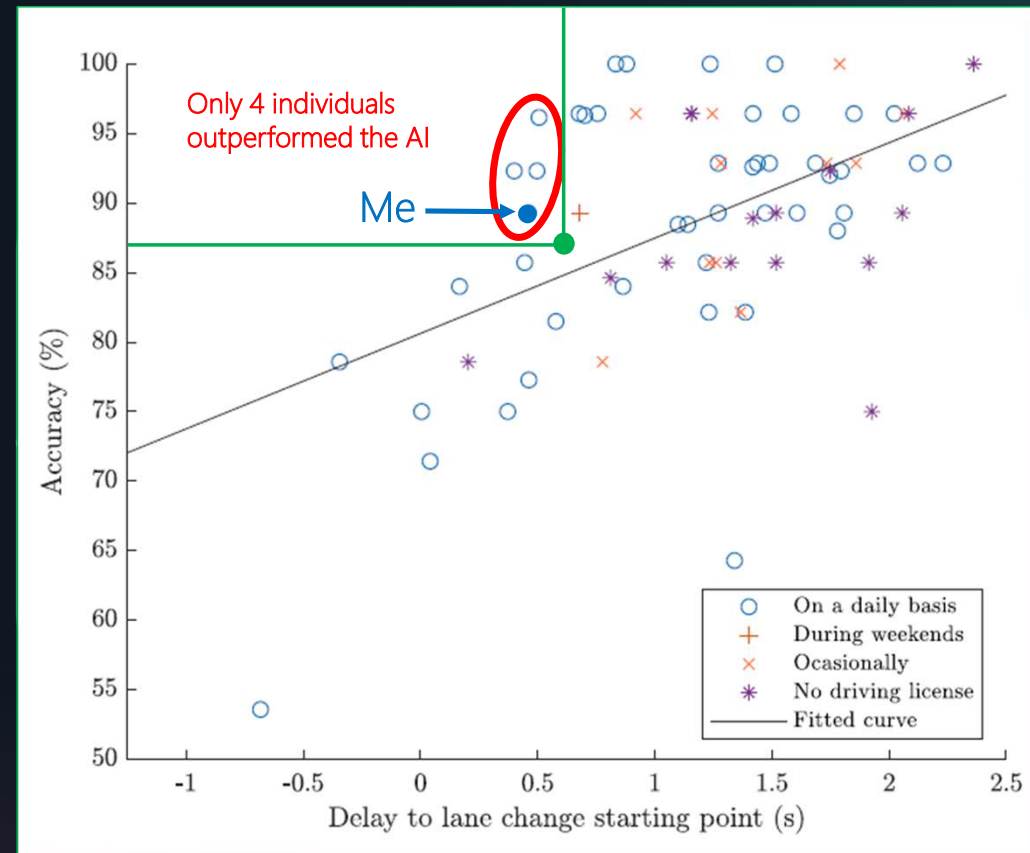
**How does AI compare to humans
in lane-change behavior prediction tasks?**

Vehicle Motion Forecast

Humans vs AI – Accuracy vs Delay

- Accuracy: 87.4 %
- Average AI delay: 0.66 s
- Average human delay: 1.08 s

AI Anticipation time with respect to average human capacity: 420 ms





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Taking a step further in Behavior Prediction

Taking a step further in behavior prediction



Use contextual information for further anticipation

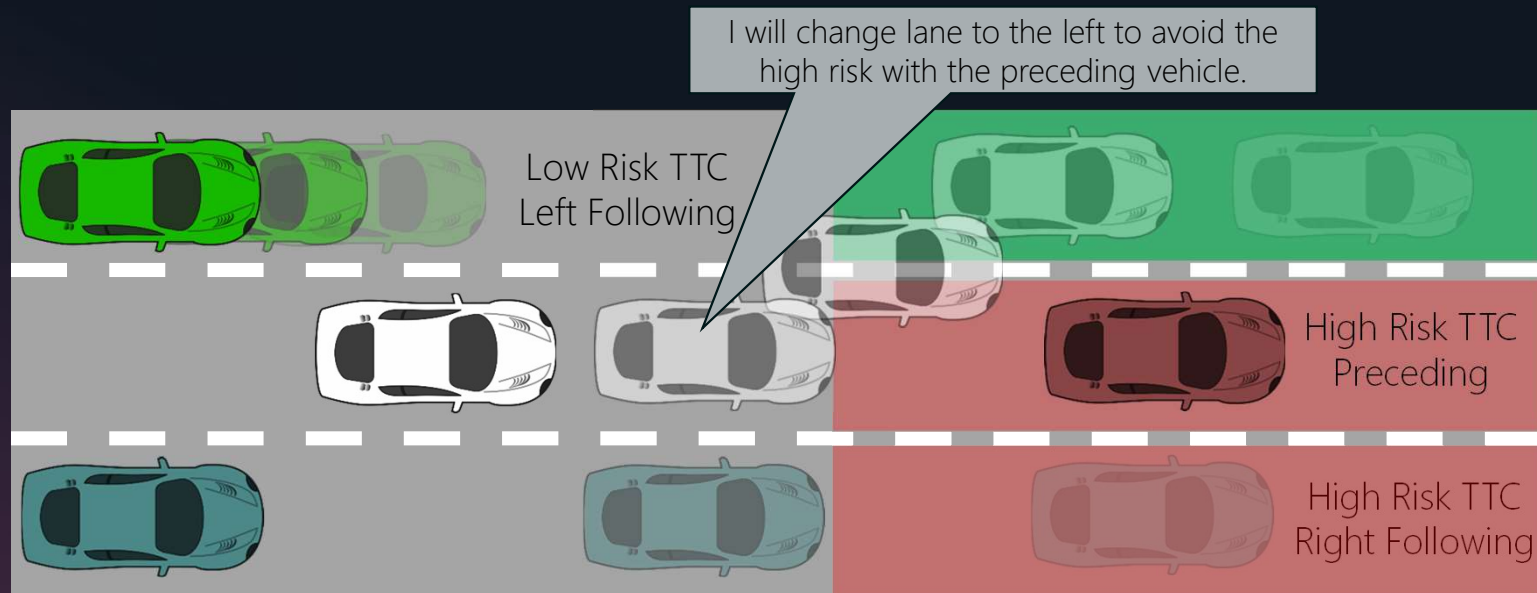


Develop explainable predictors

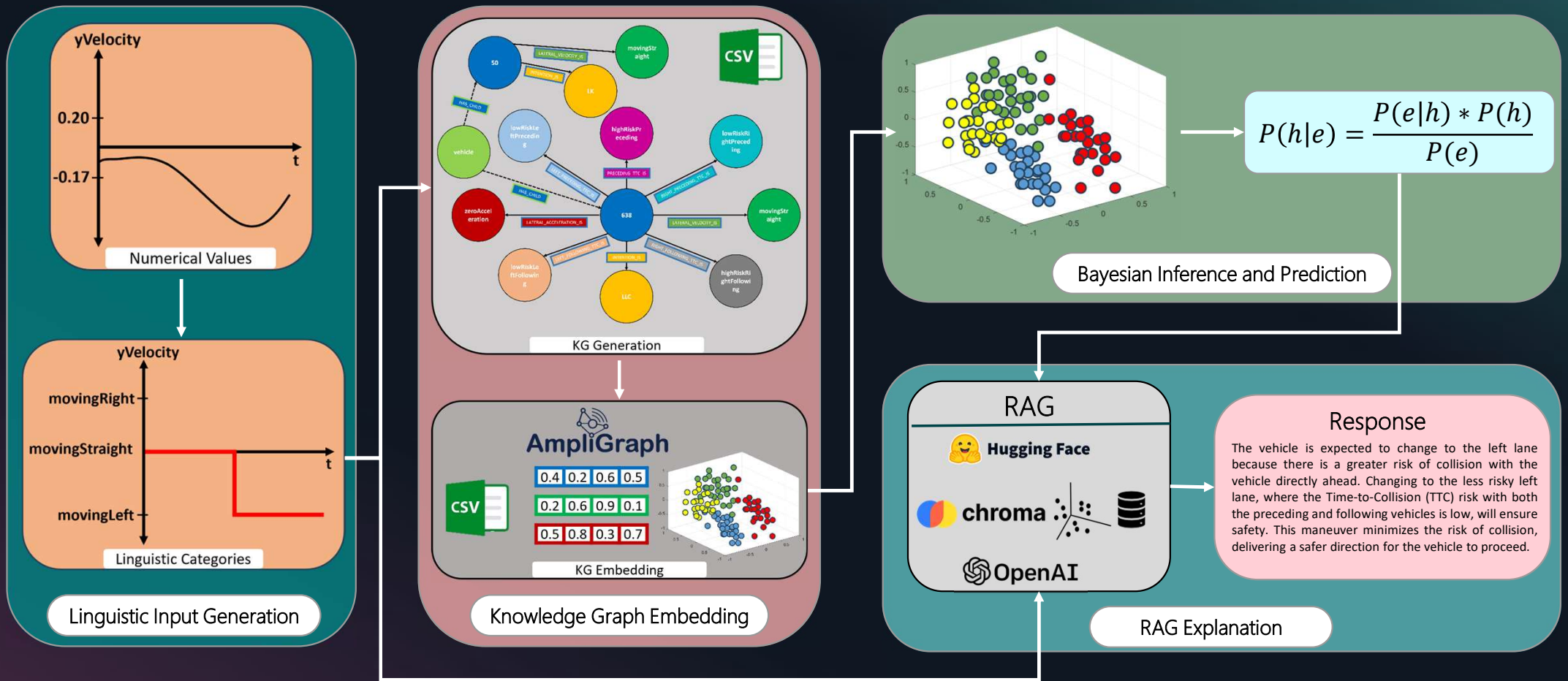


Target new use cases: near crash & occluded pedestrians

1. Anticipate behavior predictions using contextual information, as we (human drivers) do.
 - Predictions are based on Knowledge Graphs (KG). They are interpretable and explainable.
 - Bayesian inference is carried out as a downstream task on the grounds of the learned embeddings, allowing the implementation of a fully inductive reasoning system based on Knowledge Graph Embedding (KGE).
2. Providing clear explanations of the predicted behaviors in understandable human natural language.
 - Predictions will be explainable by combining KGs with Retrieval Augmented Generation (RAG) models.

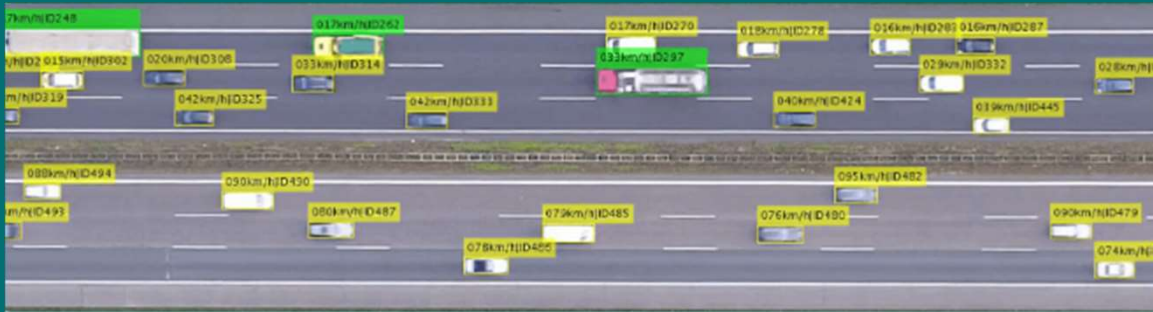


Architecture Pipeline

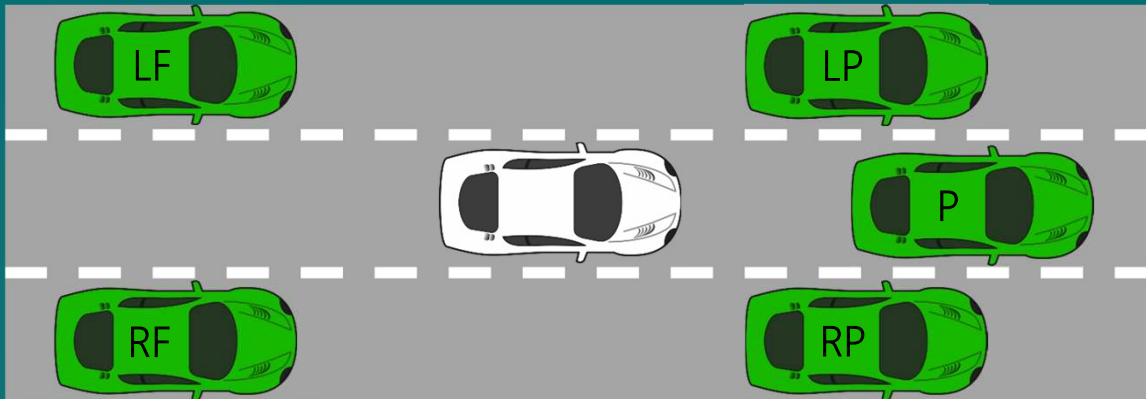
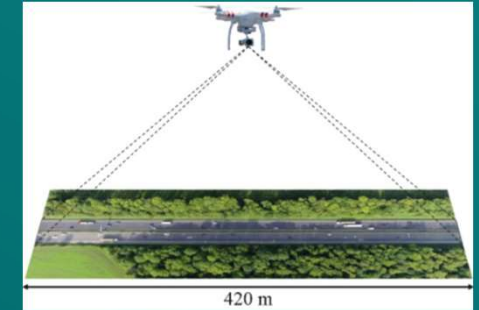


RAG: Retrieval Augmented Generation

Linguistic Input Generation

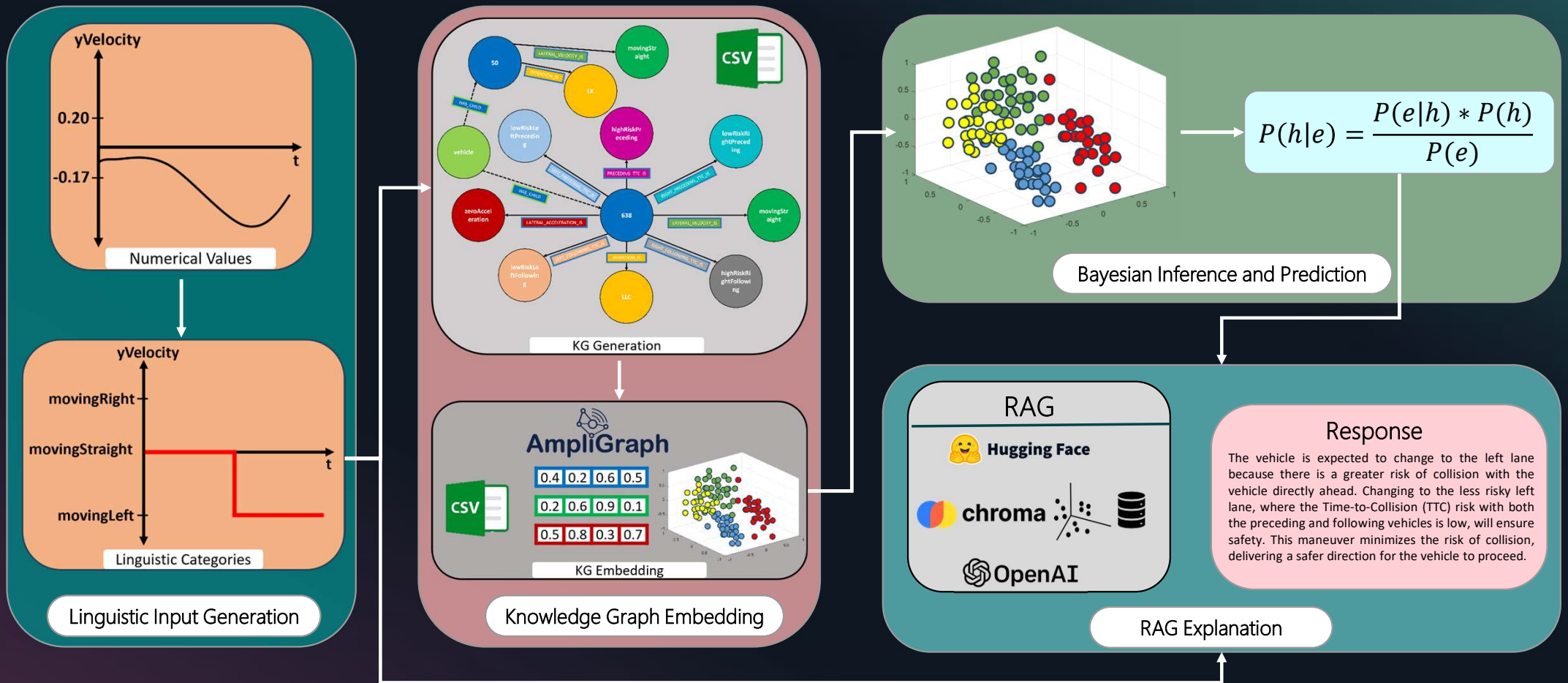


HighD Dataset



- Lateral velocity
- Lateral acceleration
- TTC with:
 - Left preceding vehicle (LP)
 - Preceding vehicle (P)
 - Right preceding vehicle (RP)
 - Left following vehicle (LF)
 - Right following vehicle (RF)

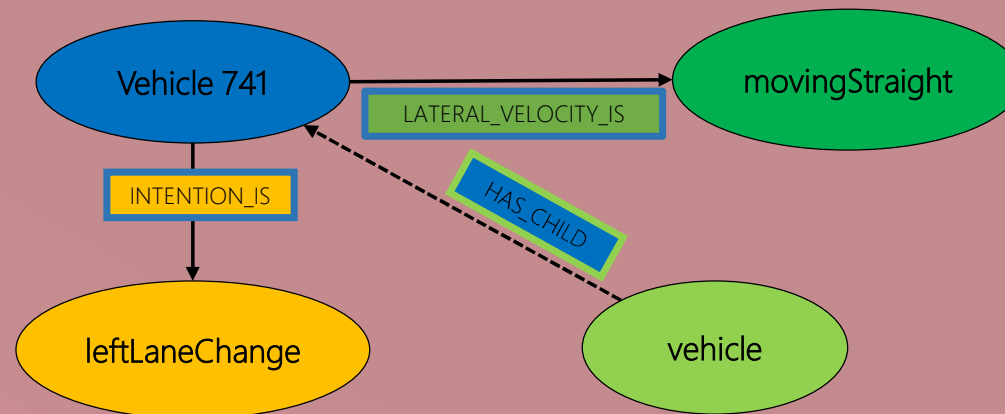
Architecture Pipeline





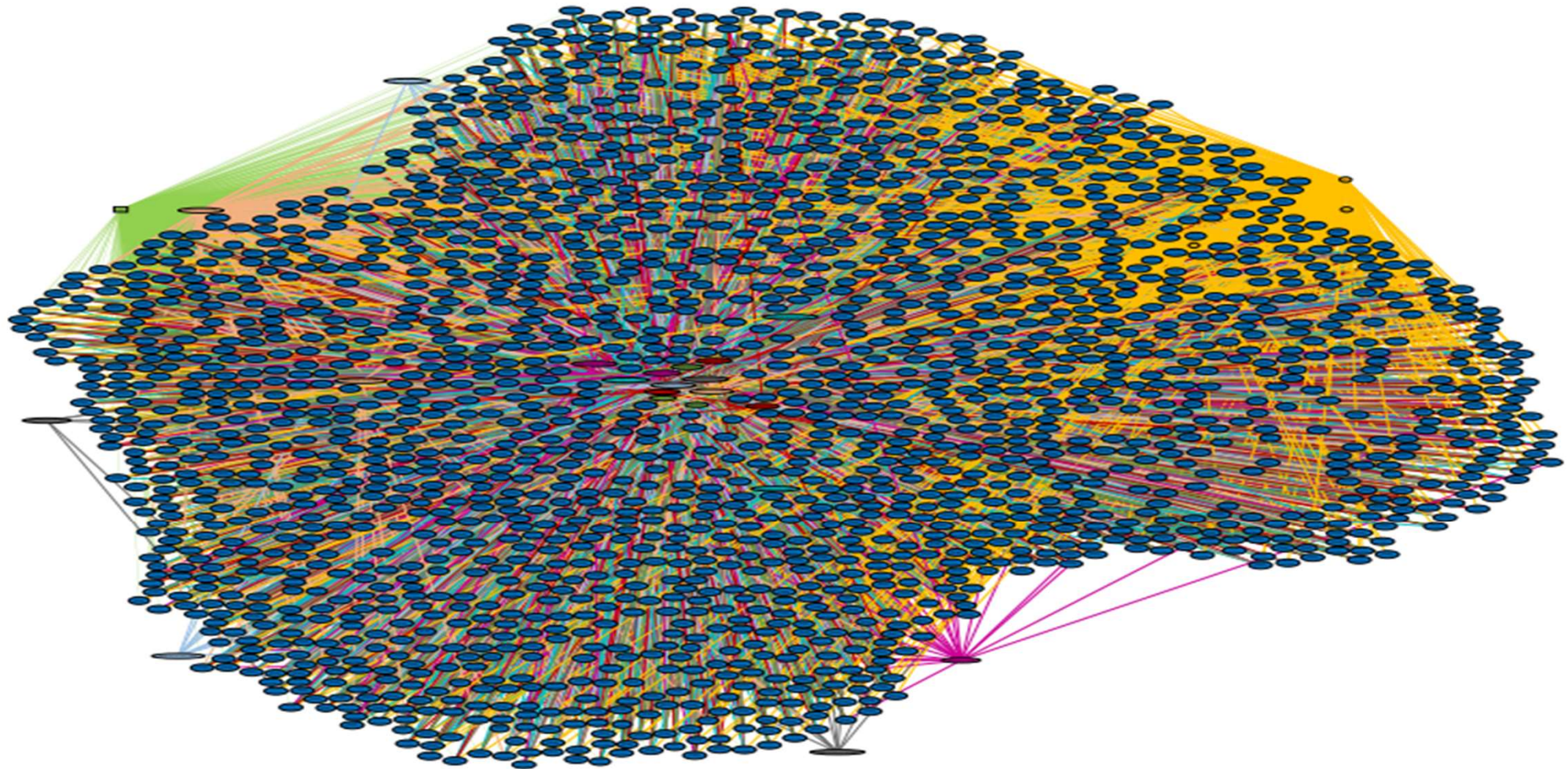
Knowledge Graphs

- A Knowledge Graph is a type of database that structures knowledge in a way that is both human-interpretable and easily analyzed.
- Example: <vehicle 741, INTENTION_IS, leftLaneChanging>
 - Subject entity: vehicle 741
 - Relation: INTENTION_IS
 - Object entity: leftLaneChanging

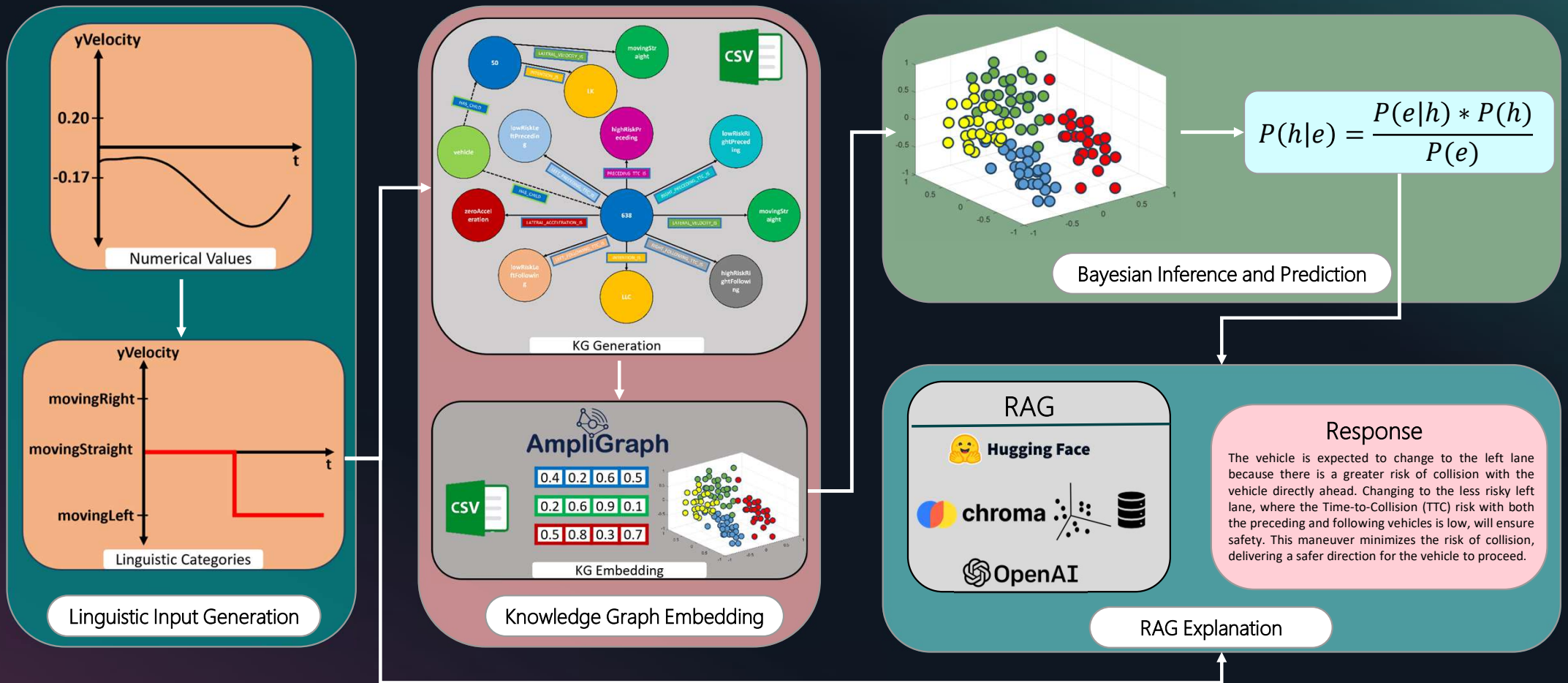


Knowledge Graph

CSV

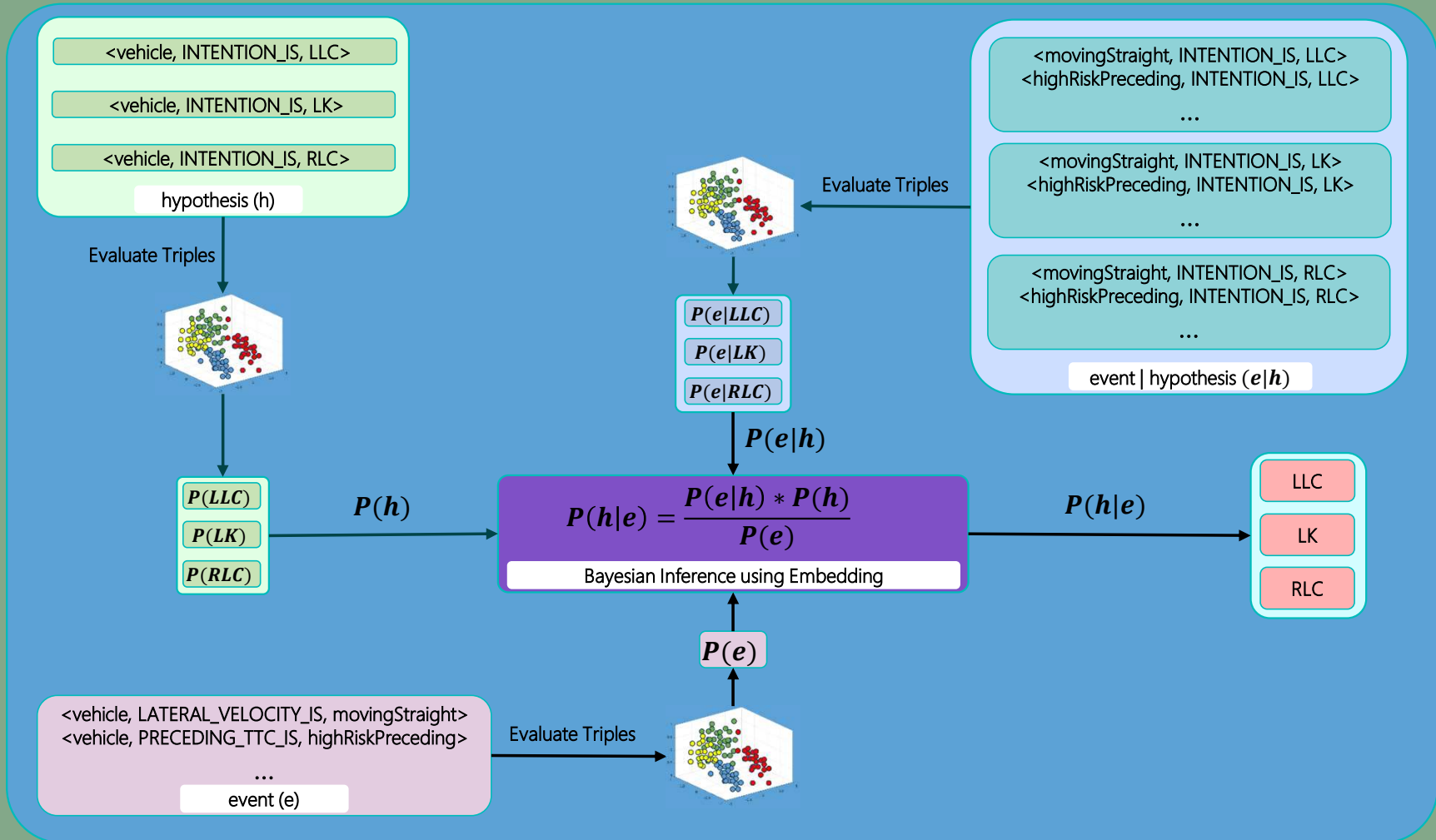


Architecture Pipeline



Bayesian Inference and Prediction

$$P(\text{hypothesis}|\text{event}) = \frac{P(\text{hypothesis}) * P(\text{event}|\text{hypothesis})}{P(\text{event})}$$



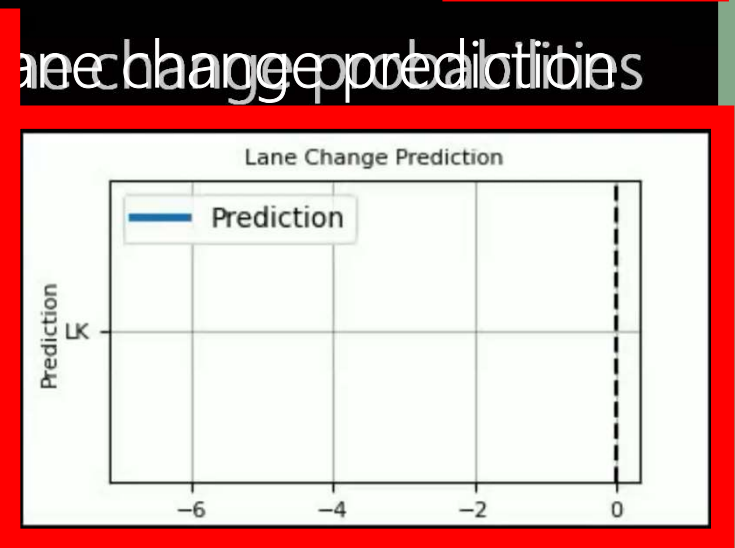
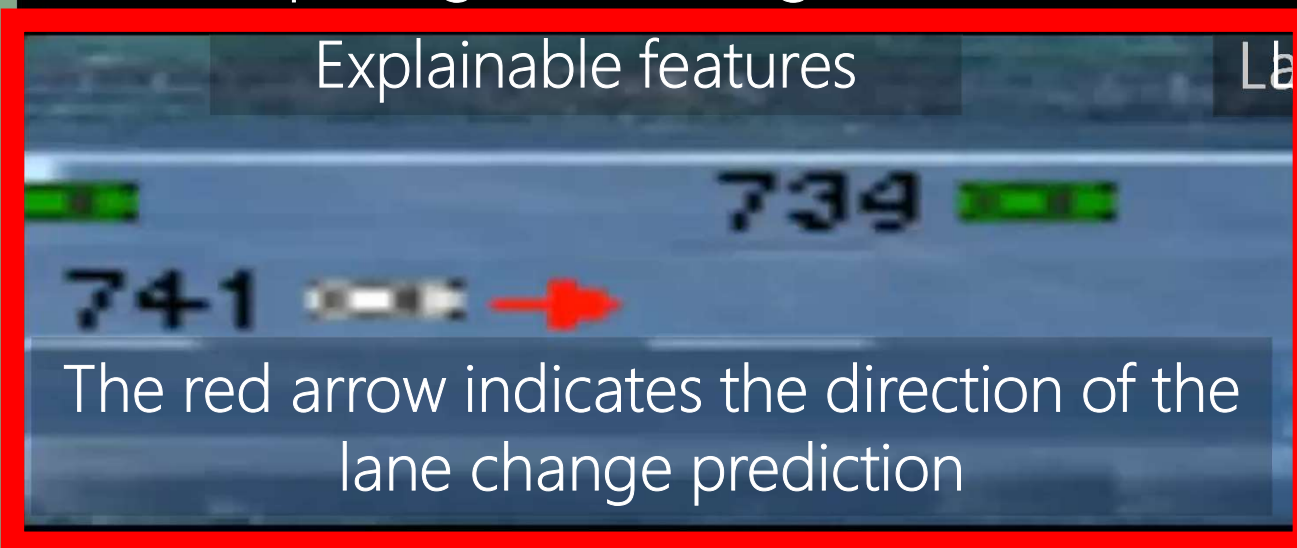
Bayesian Inference and Prediction



Close-up image of the target vehicle

straightMotion (0.17)	highRiskLeftFollowing (2)	lowRiskLeftPreceding (-5)	LLC (29%)
zeroAcceleration (-0.04)	lowRiskRightFollowing (-2)	mediumRiskPreceding (7)	LK (53%)
		lowRiskRightPreceding (19)	RLC (18%)

A dashboard-style display showing various features and their values. The features are color-coded: green for positive, red for negative, orange for positive, grey for negative, blue for negative, pink for positive, and cyan for positive. The LLC, LK, and RLC values are shown in separate colored boxes on the right.



Bayesian Inference and Prediction



straightMotion (0.09)

mediumRiskLeftFollowing (4)

lowRiskLeftPreceding (-62)

LLC (18%)

zeroAcceleration (0.04)

lowRiskRightFollowing (inf)

lowRiskPreceding (-57)

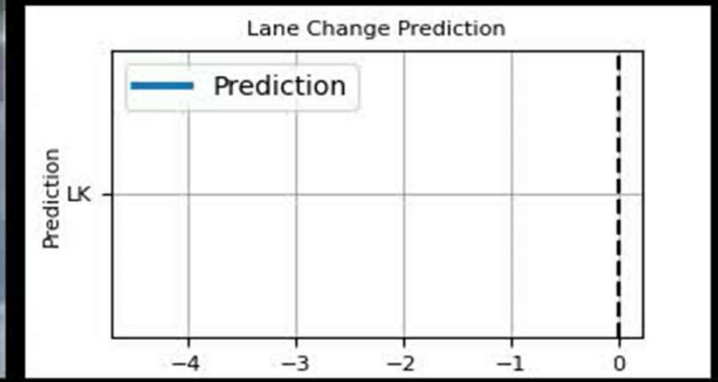
LK (64%)

lowRiskRightPreceding (-369)

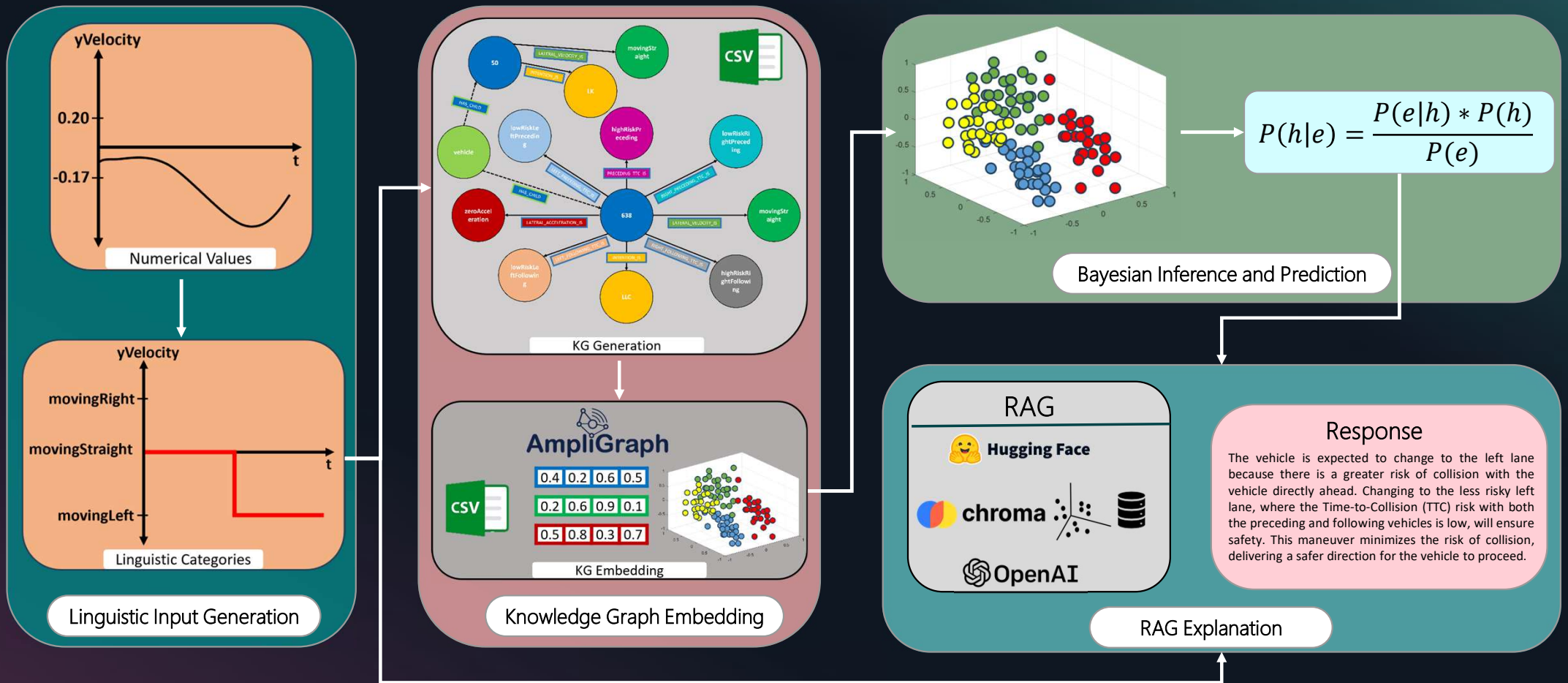
RLC (18%)



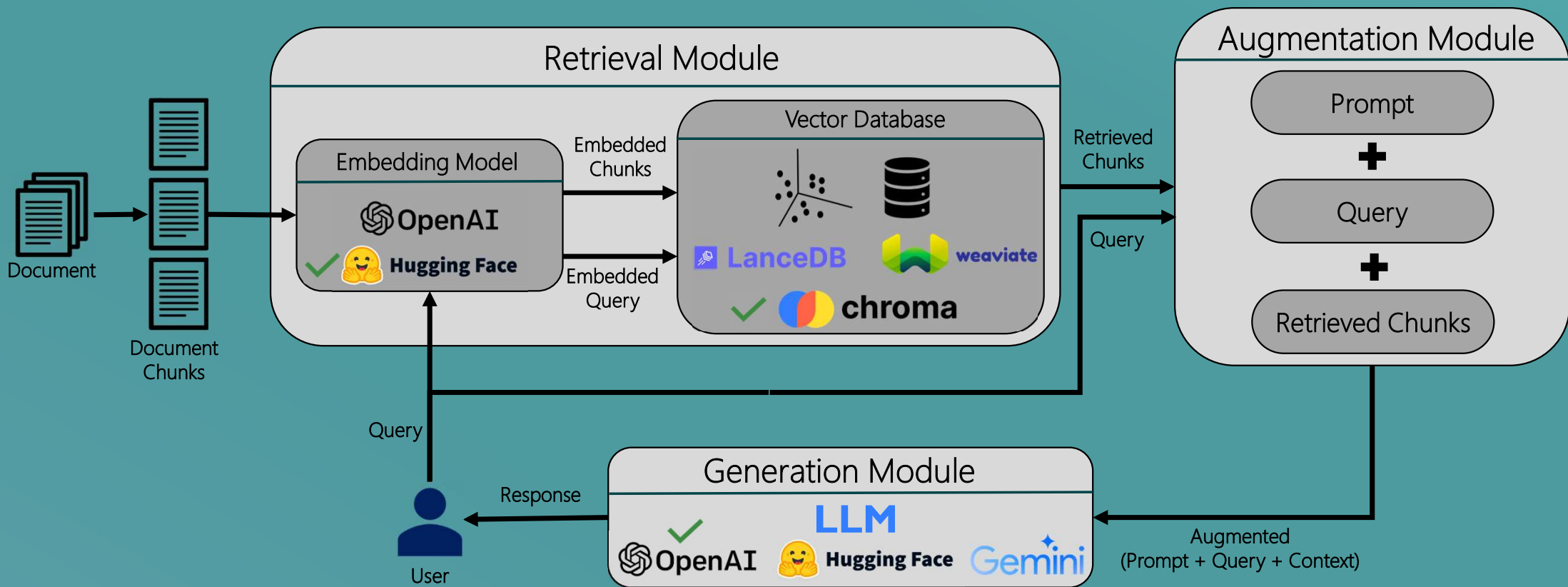
The right lane change is predicted even before the target vehicle has finished overtaking the truck.



Architecture Pipeline



RAG Explanation





Prompt

You are an expert on vehicle lane change prediction tasks and must **justify why the vehicle did one of the following maneuvers** (left lane change, or right lane change, or kept lane).

- **Context (input):** Natural text that describes the scene. The given inputs are: the target vehicle's lateral acceleration, lateral velocity, TTC (Time To Collision) risk with (left preceding, preceding, right preceding, left following, right following) surrounding vehicles, and the target vehicle's predicted lane change maneuver. (high TTC is the highest risk level, medium TTC is risky as well but is less than high, low TTC indicates no risk).

- **Output:** Justification of the lane change maneuver in clear and precise English with a maximum of 75 words.

- **Command:** State the main reasons contributing to the anticipated vehicle maneuver. **Take the retrieved scenarios as supporting scenes.** Follow the next example while generating your output.

- **Example:**

Input: Explain the reason why the vehicle will make a left lane change, given the following prior information:

- * The vehicle has zero lateral acceleration.
- * The vehicle is moving straight.
- * The TTC risk from the left preceding vehicle is low.
- * The TTC risk from the preceding vehicle is medium.
- * The TTC risk from the right preceding vehicle is low.
- * The TTC risk from the left following vehicle is low.
- * The TTC risk from the right following vehicle is low.

Output: (The vehicle will initiate a left lane change in response to the small gap with the vehicle directly ahead, which **elevates the risk** of the current situation. However, the left lane presents a **safer option** because the Time-to-Collision (TTC) risk associated with both the preceding and following vehicles in that lane is low. This provides a **more secure gap for the maneuver**. Consequently, transitioning to the left lane is the best option.)

RAG Explanation



Hugging Face



chroma



OpenAI



Query

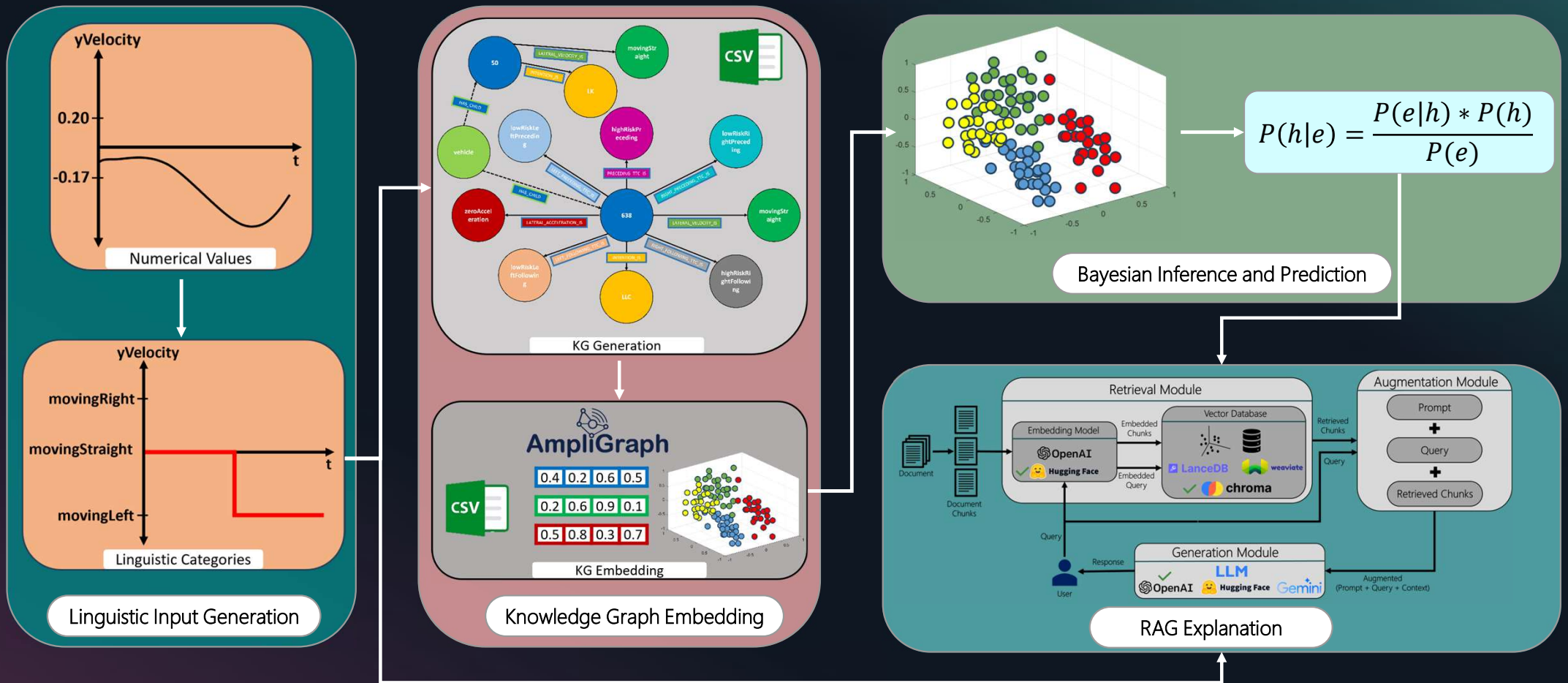
Explain the reason why the vehicle will make a left lane change maneuver, given the following prior information:

- * The vehicle is not accelerating in the lateral direction.
- * The vehicle is moving straight.
- * The TTC risk from the left preceding vehicle is low.
- * The TTC risk from the **preceding vehicle is medium**.
- * The TTC risk from the right preceding vehicle is low.
- * The TTC risk from the left following vehicle is low.
- * The TTC risk from the right following vehicle is low.

Response

The vehicle is expected to change to the left lane **because there is a greater risk of collision with the vehicle directly ahead. Changing to the less risky left lane**, where the Time-to-Collision (TTC) risk with both the preceding and following vehicles is low, **will ensure safety**. This maneuver minimizes the risk of collision, delivering a safer direction for the vehicle to proceed.

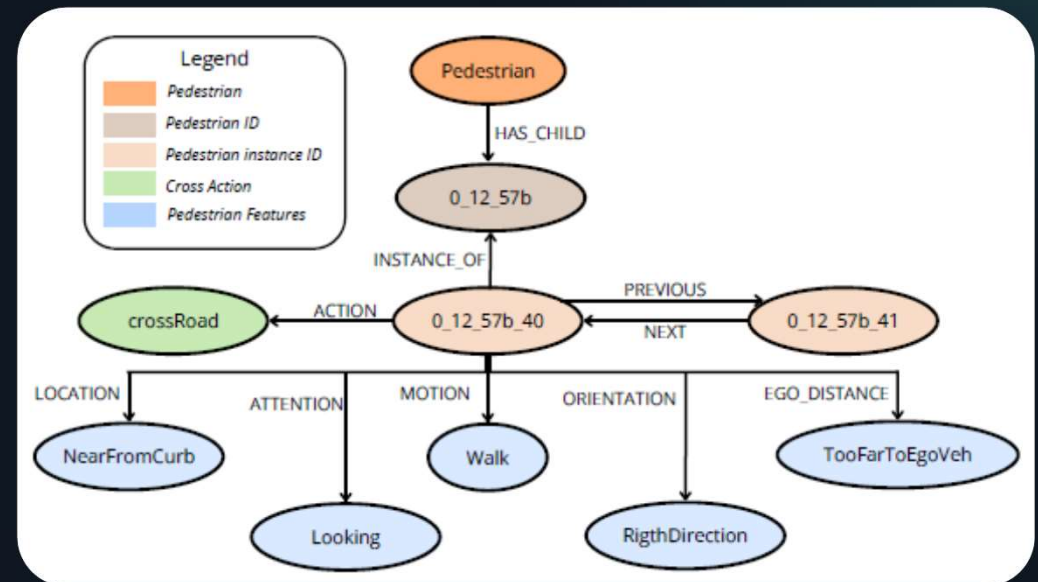
Architecture Pipeline



Prediction of pedestrians' crossing intentions

Expressive Features

- Attention: looking at driver
- Motion activity: walk, stand, run, waive
- Location: near/far from curb
- Orientation: with respect to the road
- Distance: near/far from ego-vehicle
- Type: regular adult, child
- Capability: regular, crutches, wheelchair



RAG-based prediction explanation

Prompt

You are an expert on the pedestrian behavior on the road and you are an expert assistant for question-answering tasks.

- **Context (input):** Natural text that describes the scene. Linguistic inputs describe the pedestrian state: orientation, gaze, action, proximity to the road and distance.

- **Output:** Justification of the pedestrian crossing behavior in clear and precise English with a maximum of 75 words and do not use conditional words as may

- **Command:** Use the following pieces of retrieved context to answer the question. If you don't know the answer, just say that you don't know.

- Example:

Input: Explain the reason why a pedestrian will not cross the street, given the following prior information:

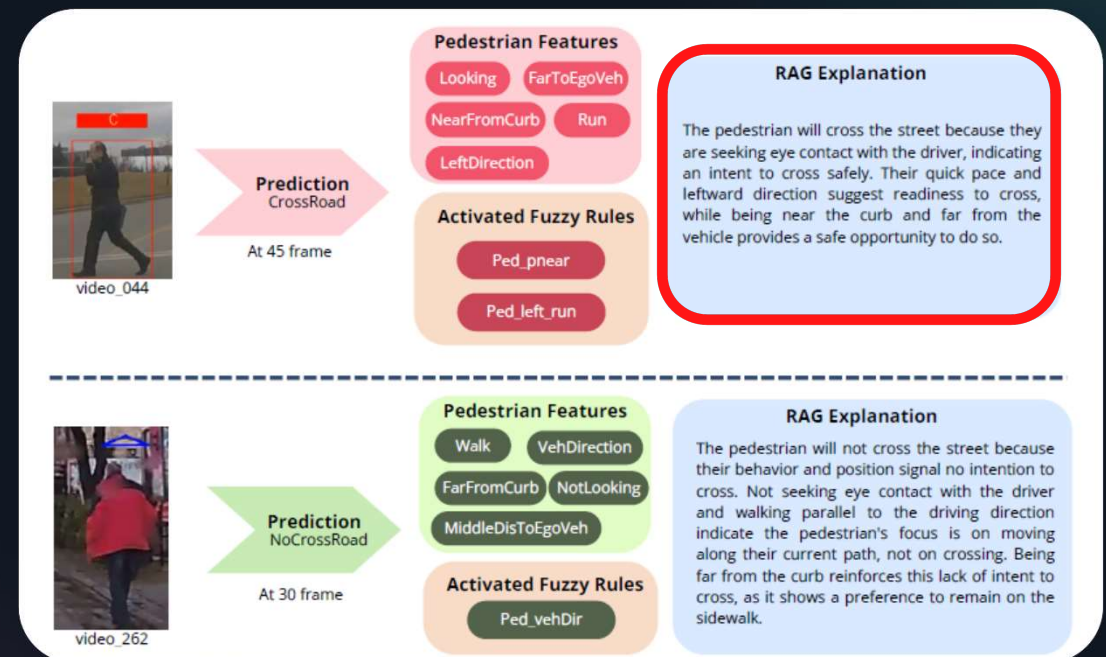
- The pedestrian is looking at the driver for eye contact
- The pedestrian is standing in a leftward direction
- The pedestrian is located at a near distance from the curb
- The pedestrian is far from the vehicle

Output: The pedestrian will not cross the street because they are seeking eye contact with the driver, indicating a need for assurance of safety before crossing. Standing in a leftward direction suggests they are not yet ready to cross, possibly waiting for the right moment or assessing the vehicle's distance and speed. Being far from the vehicle, they might judge it unsafe or premature to cross due to the distance, preferring to wait until the vehicle is closer or has passed.

Query

Explain the reason why a pedestrian will cross the street, given the following prior information:

- The pedestrian is looking at the driver for eye contact.
- The pedestrian is walking quickly in a leftward direction.
- The pedestrian is located at a near distance from the curb.
- The pedestrian is far from the vehicle





Pedestrians Expressive Features

Prediction of pedestrians' crossing intentions



New use cases – Context-based



Prediction of near-crash



Prediction of occluded pedestrians

Prediction of near-crash situation

Contextual variables

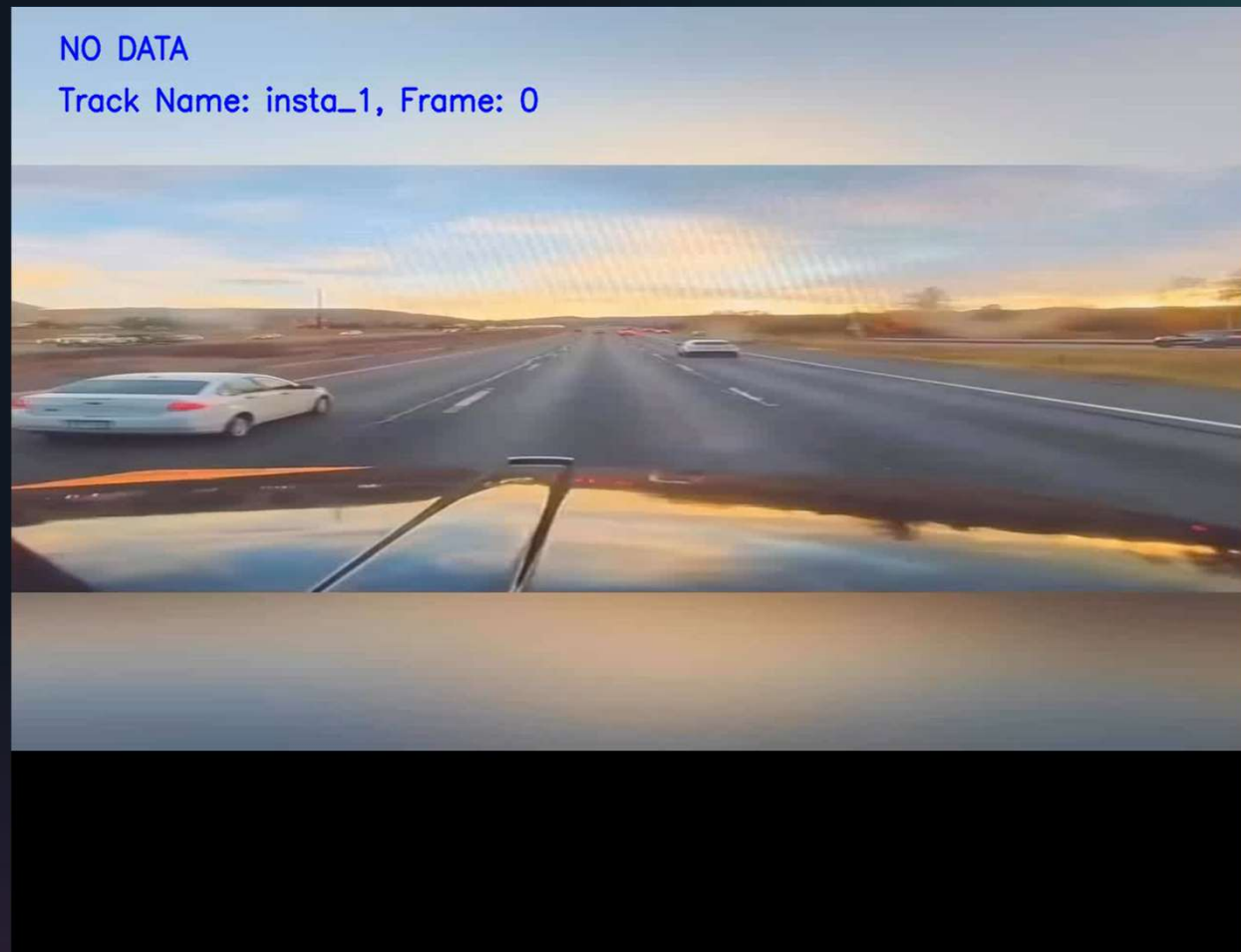
- Congested adjacent lane
- Activation of braking lights
- Free ego-vehicle lane
- Fast approaching



Prediction of near-crash situation

Contextual variables

- Congested adjacent lane
- Activation of braking lights
- Free ego-vehicle lane
- Fast approaching



MPC-based near-crash reaction

Frame Number: 0

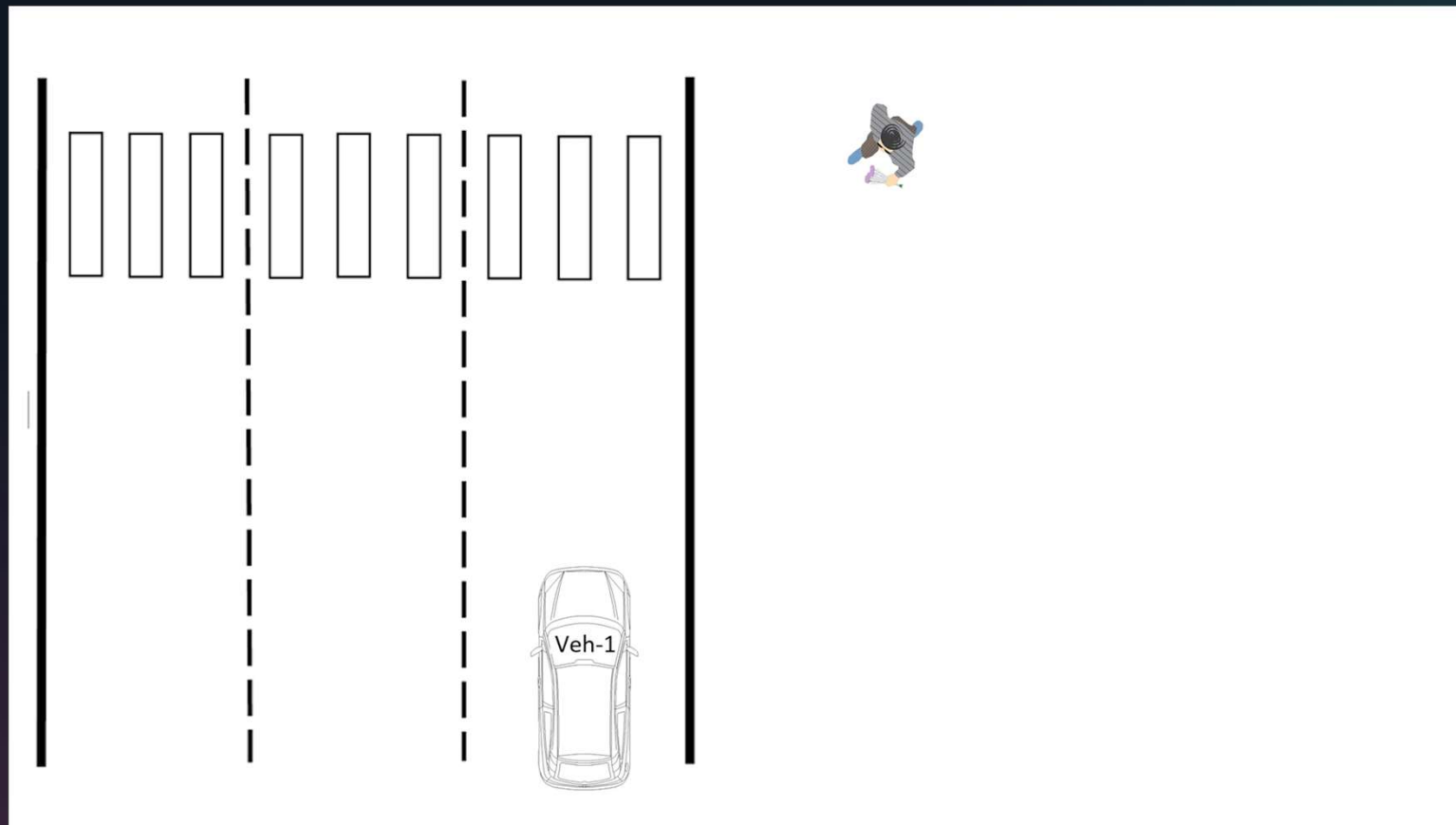


MPC-based near-crash reaction

Frame Number: 0



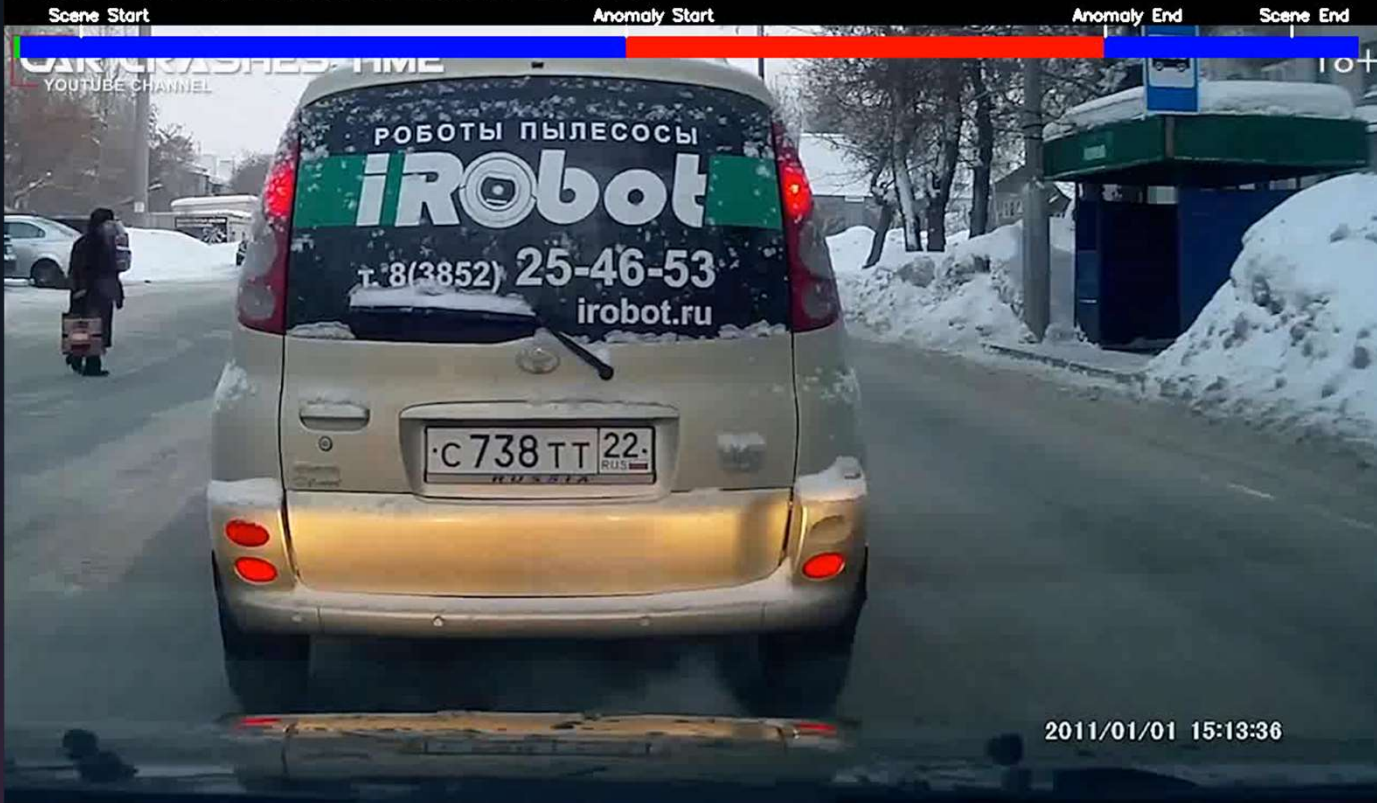
Prediction of occluded pedestrians



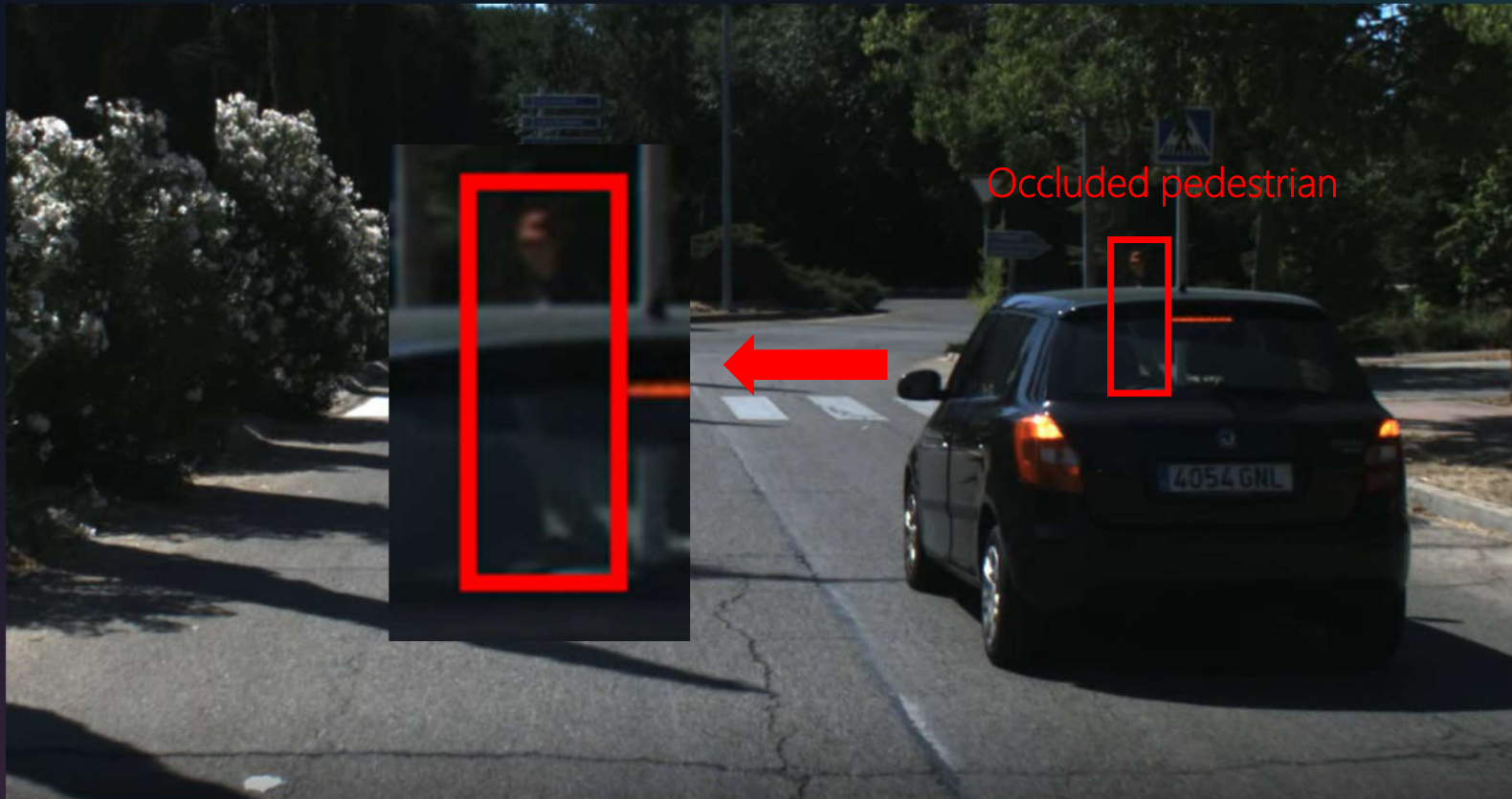


Prediction of occluded pedestrians

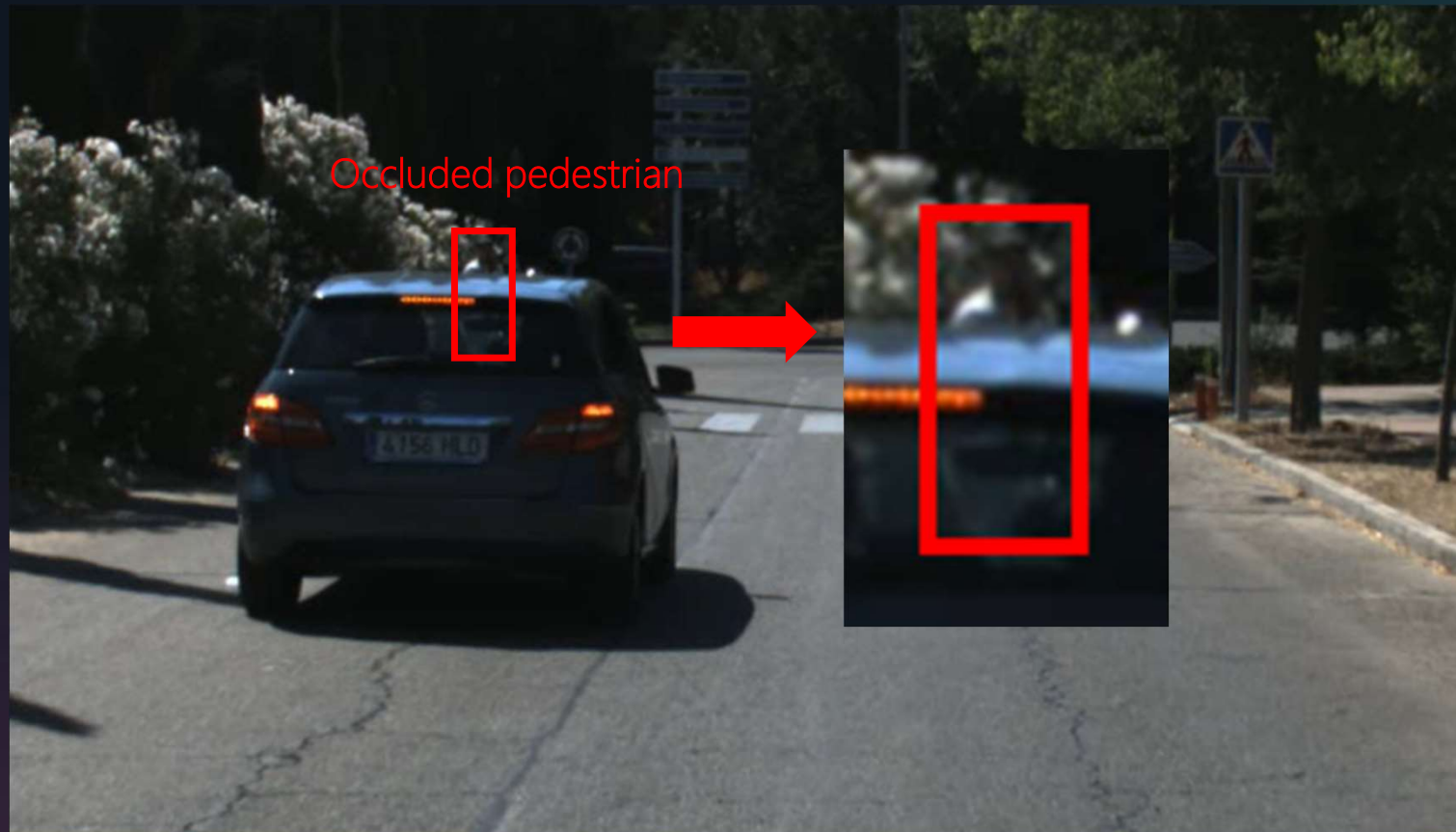
Video Name: 3tEZvtQZ18Q_004095, Ignore: No, Ego Vehicle: Ego Not Involved
Accident Type: pedestrian
Anomaly Start: 46, Anomaly End: 82
Frame ID: 0, Accident Name: normal



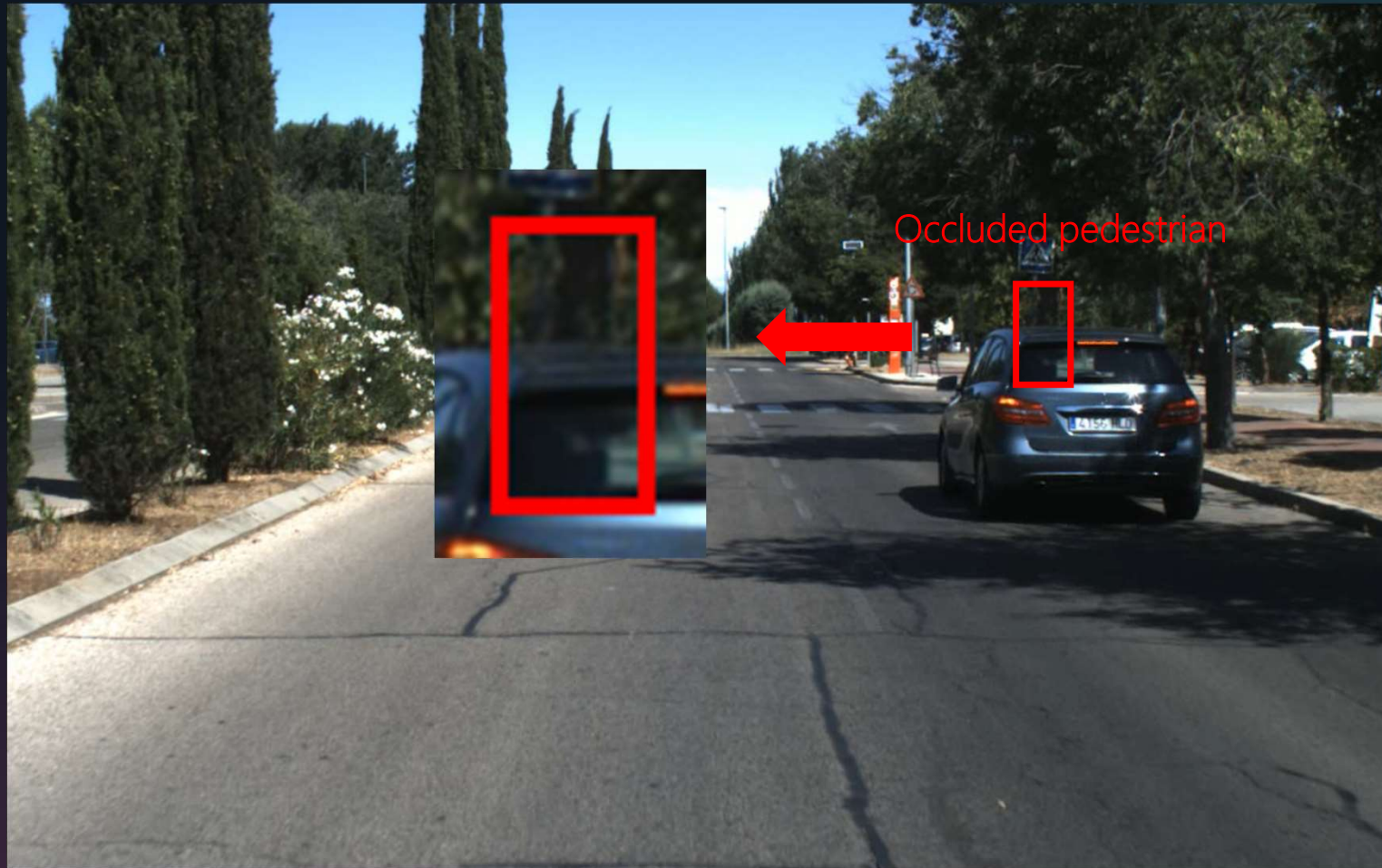
Prediction of occluded pedestrians



Prediction of occluded pedestrians



Prediction of occluded pedestrians



Prediction of occluded pedestrians

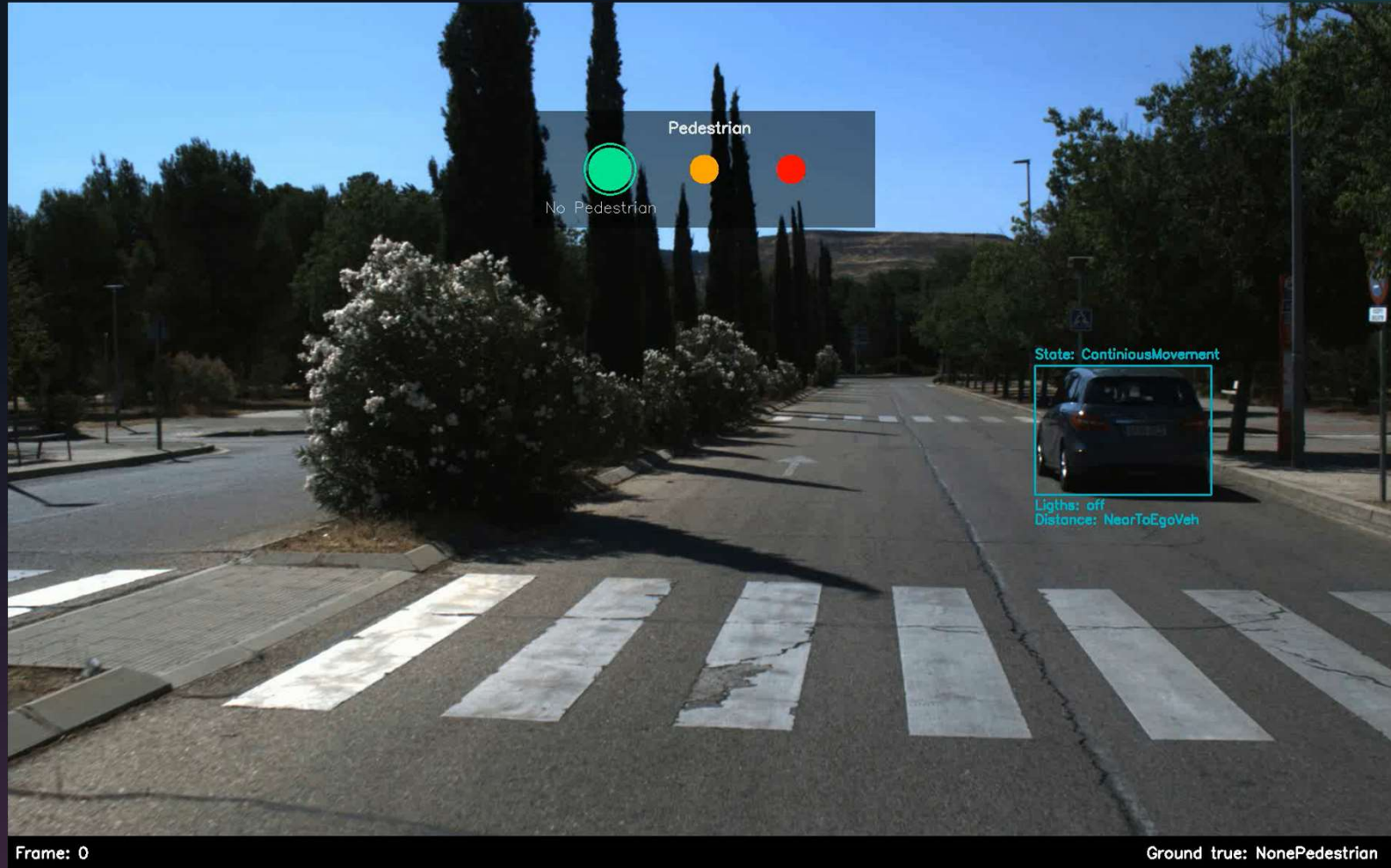


Prediction of occluded pedestrians

Contextual variables

- Presence of crosswalk
- Presence of vegetation or other sight-occluding elements
- Activation of braking lights in preceding vehicle
- Preceding vehicle deceleration and velocity
- Distance to preceding vehicle
- Number of lanes
- Free lane in front of preceding vehicle
- Free ego-lane ahead

Prediction of occluded pedestrians



Prediction of occluded pedestrians





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Prediction as a key for Optimal Interactions

From Predictions to Interactions

UNDERSTANDING BEHAVIOR IS KEY FOR OPTIMIZING INTERACTIONS BETWEEN AVs AND ROAD USERS



HMI strategies



Motion Behavior

HEIDI



HOLISTIC AND **A**DAPTIVE **I**NTERFACE **D**ESIGN FOR HUMAN-TECHNOLOGY **I**NTERACTION



This project has received funding from the European Union's Horizon Europe research and innovation program with ID 101069538



HEIDI

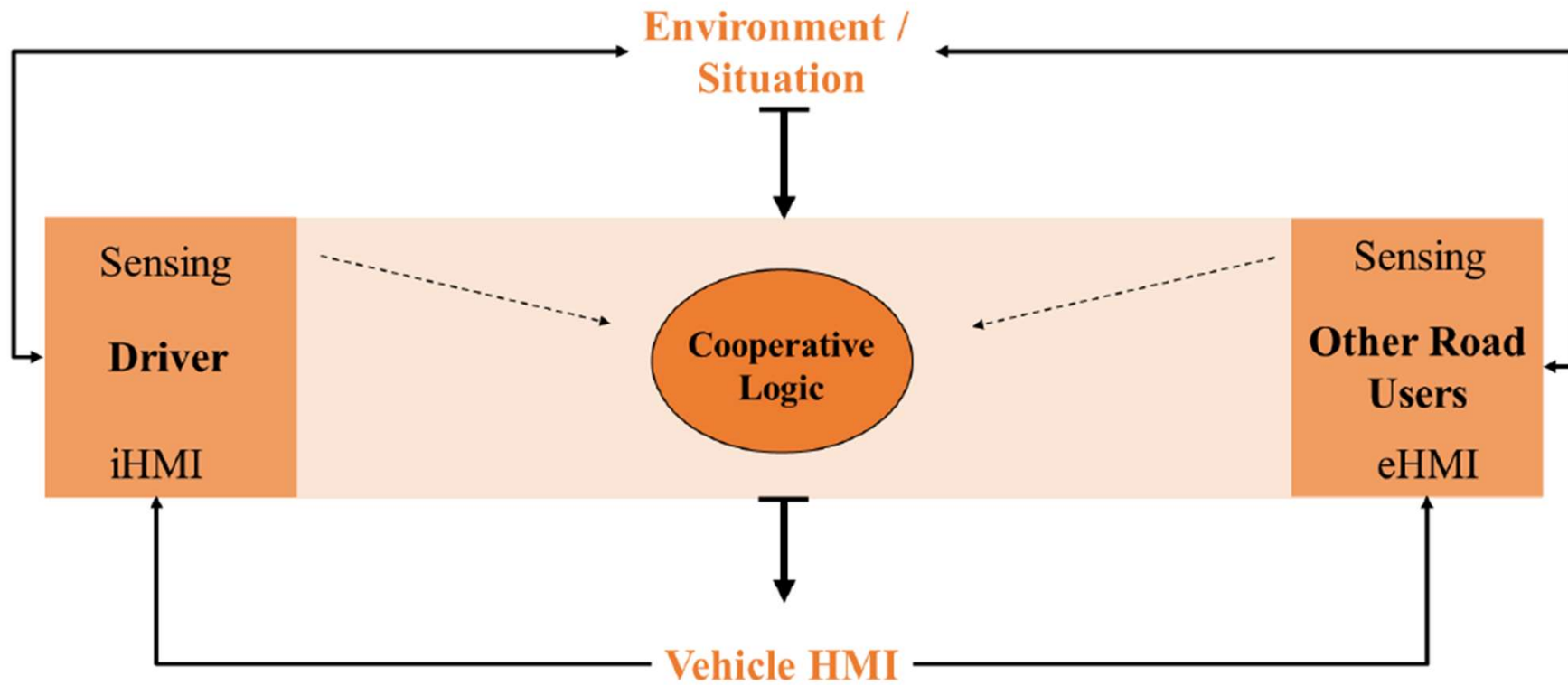
2022 - 2025





HEIDI

2022 - 2025





External Sensing – Environment Detection (Road, Cars, Infrastructure)

External Sensing – VRU Detection

External Sensing – VRU Type

External Sensing – VRU Intention/Prediction

External Sensing – VRU Attention/State

Internal Sensing – Driver State/Attention


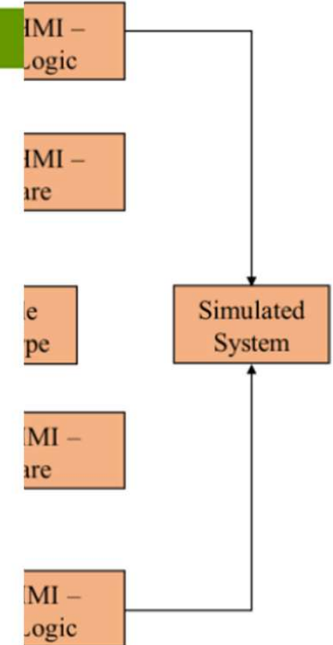
Internal Sensing – Driver Intention/Behaviour Prediction

Homepage Organizer FAQ

Competition Results and Ceremony

- Track 1 [Top 1-3]:
 - Queen Mary University of London [Leader: Chiang, Chiayen]
 - The Hong Kong Polytechnic University [Leader: Hu, Fengqing]
 - Nan Jing University [Leader: Jin, Zhiyu]
- Track 2 [Top 1-3]:
 - Kookmin University [Leader: Lee, Seungju]
 - Southeast University [Leader: Ji, Yufei]
 - Chongqing University of Technology [Leader: Du, Xin]
- Track 3 [Top 1]:
 - University of Alcalá [Leader: Manzour Hussien, Mohamed]
- Honorable Mention List:
 - University of Alcalá [Leader: MELO CASTILLO, Angie Nataly]
 - Peking University [Leader: Zhang, Jinyan]
 - Tianjin Normal University [Leader: Zhou, Jianglin]

The detailed prize information will be announced in ITSC 2023 workshop - 3rd Workshop On The Prediction Of Pedestrian Behaviors For Automated Driving.



The path forward in SCAVs

- Leverage ADAS for shaping social norms and for accelerating drivers' adaptation to local traffic rules.
 - Reinforcement of Injunctive norms.
- Development of AVs capable of negotiating with other road users while abiding by the local social norms.
 - Neuro-symbolic reasoning (traffic rules, social norms, common sense).

Thanks – Q&A



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