A Hybrid-AI Approach for Competence Assessment of Automated Driving Functions

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Automated driving functions rely on logic-based and data-driven algorithms.

Deep Neural Network tends to be overconfident, especially in classification tasks [1]. It cannot reason on whether it is competent in a given situation.

CONTEXT

Report “Who’s in control?”, Dutch Safety Board
November 28th, 2019 The Hague
HYBRID AI [2]

- **Use case**: cut-in classification.
- **Goal**: competence assessment of a Deep Neural Network in a variety of situations.
- **Method**: coupling a data-driven approach to a knowledge graph to return an estimate of the classifier reliability.

<table>
<thead>
<tr>
<th>Hybrid AI</th>
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</thead>
<tbody>
<tr>
<td><strong>Data-driven</strong></td>
</tr>
<tr>
<td>- Out-of-distribution analysis</td>
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<tr>
<td><strong>Knowledge-driven</strong></td>
</tr>
<tr>
<td>- Ontology-based knowledge graph</td>
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</table>
**FRAMEWORK**

**PERCEPTION**

- **Feature Uncertainty Estimator** quantifies the extent to which an observation is out-of-distribution.

  ![Density of feature acceleration graph]

- We fit a Kernel Density Estimator (KDE) over all the features in the training data.

- We derive the normalized likelihood of a new observation $x$.

Deep Neural Networks underperform on out-of-distribution data.
REASONING

Reasoning relies on an **ontology-based knowledge graph**.

- Ontology allows to inject domain expert knowledge for semantic inference.
- The world is structured in *entities* [e.g. vehicle, lane] and *attributes* [e.g. visibility of the lane] connected via *relations* [e.g. drives_on_lane].
**FRAMEWORK**

**REASONING**

Reasoning relies on an **ontology-based knowledge graph**.  

- Ontology allows to inject domain expert knowledge for semantic inference.
- The world is structured in *entities* [e.g. vehicle, lane] and *attributes* [e.g. visibility of the lane] connected via *relations* [e.g. drives_on_lane].

We adopted inference rules [3] to:

- Assign “importance” (categorical) and “doubt” (numerical) attributes to the entities and relations based on **domain knowledge**.
- Combine *importance* and *doubt* into a measure of *competence*. 
FRAMEWORK

REASONING

Importance → Risk posed

- High
- Low

EV
A Hybrid-AI Approach for Competence Assessment of Automated Driving Functions

FRAMEWORK

REASONING

Importance → Risk posed

- High
- Low

Truck 1

EV

0.75
FRAMEWORK

REASONING

Ev

Importance → Risk posed

- High
- Low

Truck 1

EV

0.75

0.9

Entrance lane
FRAMEWORK

REASONING

![Diagram of road scenario with vehicles and risk assessment]

**Importance → Risk posed**

- **High**
- **Low**

- **EV lane**: Low risk (0.1)
- **Entrance lane**: High risk (0.9)
- **Truck 1**: High risk (0.75)
- **Truck 2**: High risk (0.75)
- **Motorcycle**: High risk (0.9)
FRAMEWORK

DECISION MAKING

Situational-aware Competence Assessment Framework

Intention Predictor
- Cut-in Classifier
- Feature Uncertainty Estimator (univariate densities)

Reasoner and Situational Awareness

Competence Assessment
- Remember
- Forecast
- Decide

Observations: target vehicle data, road geometry, and lane visibility

Competence: cut-in yes/no, feature uncertainty

Autonomous or takeover
The doubt and importance values are combined via a weighted average to compute a current competence value (embedding). A linear regression algorithm predicts the future competence (forecasting).

Control should be handed over to the human driver when competence < \( \tau \)
**USE CASES**

<table>
<thead>
<tr>
<th>Case</th>
<th>Potential Risk</th>
<th>Reasoner</th>
<th>Competence</th>
<th>Out-of-distribution measure*</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Low</td>
<td>not present</td>
<td>-</td>
<td>0.57</td>
<td>takeover</td>
</tr>
<tr>
<td>2</td>
<td>Low</td>
<td>present</td>
<td>0.84</td>
<td>0.57</td>
<td>AD mode</td>
</tr>
</tbody>
</table>

- **Without** the Reasoner, the competence is represented by the out-of-distribution measure that depends on the Feature Uncertainty. Our approach suggests to hand the control over to the driver.

- **With** the Reasoner, the situation is evaluated and the competence results higher than the feature uncertainty.

* 1 – Feature Uncertainty
CONCLUSION

- Novel **Hybrid-AI** framework for the safe application of AI functions in automated driving.

- The Reasoner enhances the estimate of the risk.

- Solid starting point for future investigation of situational awareness.
REFERENCES


THANK YOU
AND DRIVE SAFE!
LIMITATIONS AND FUTURE WORK

- Increase the number and variety of use cases.
- Graph Neural Networks can be explored to potentially improve the competence assessment.
- Real-life data will be used in the future to move from simulation to real-life.