FORMALIZING MULTIMODAL KNOWLEDGE IN TRAFFIC SEQUENCE CHARTS FOR IMPROVING PERFORMANCE, SAFETY AND TRUSTWORTHINESS OF AI DRIVING FUNCTIONS

Dominik Grundt,
DLR – Institute Systems Engineering for Future Mobility (Oldenburg, Germany)

34th SafeTRANS Industrial Day (2024), Munich

DLR

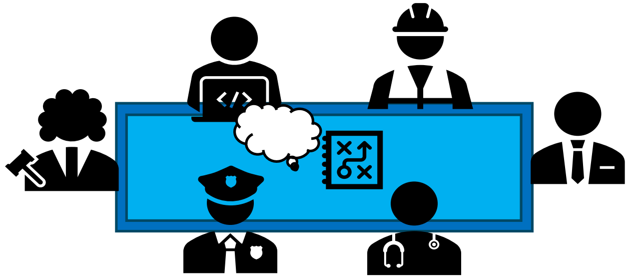
Motivation

- Automotive AI needs huge amount of data for learning
- Coverage of all situations is not possible

Motivation

- Automotive AI needs huge amount of data for learning
- Coverage of all situations is not possible
- Humans learn via experiences and observations, while considering general rules and laws

https://www.manager-magazin.de/unternehmen/autoindustrie/selbstfahrendes-kfz-mensch-vs-maschine-wer-gefahren-besser-erkennt-a-1200362.html

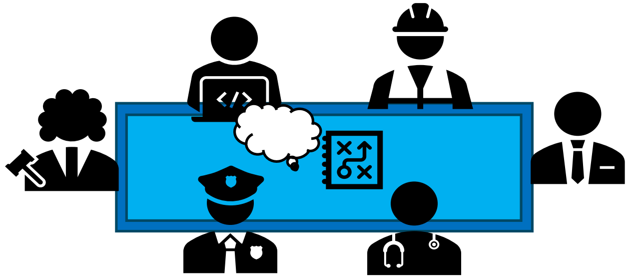


Motivation

- Automotive AI needs huge amount of data for learning
- Coverage of all situations is not possible
- Humans learn via experiences and observations, while considering general rules and laws

https://www.manager-magazin.de/unternehmen/autoindustrie/selbstfahrendes-kfz-mensch-vs-maschine-wer-gefahren-besser-erkennt-a-1200362.html

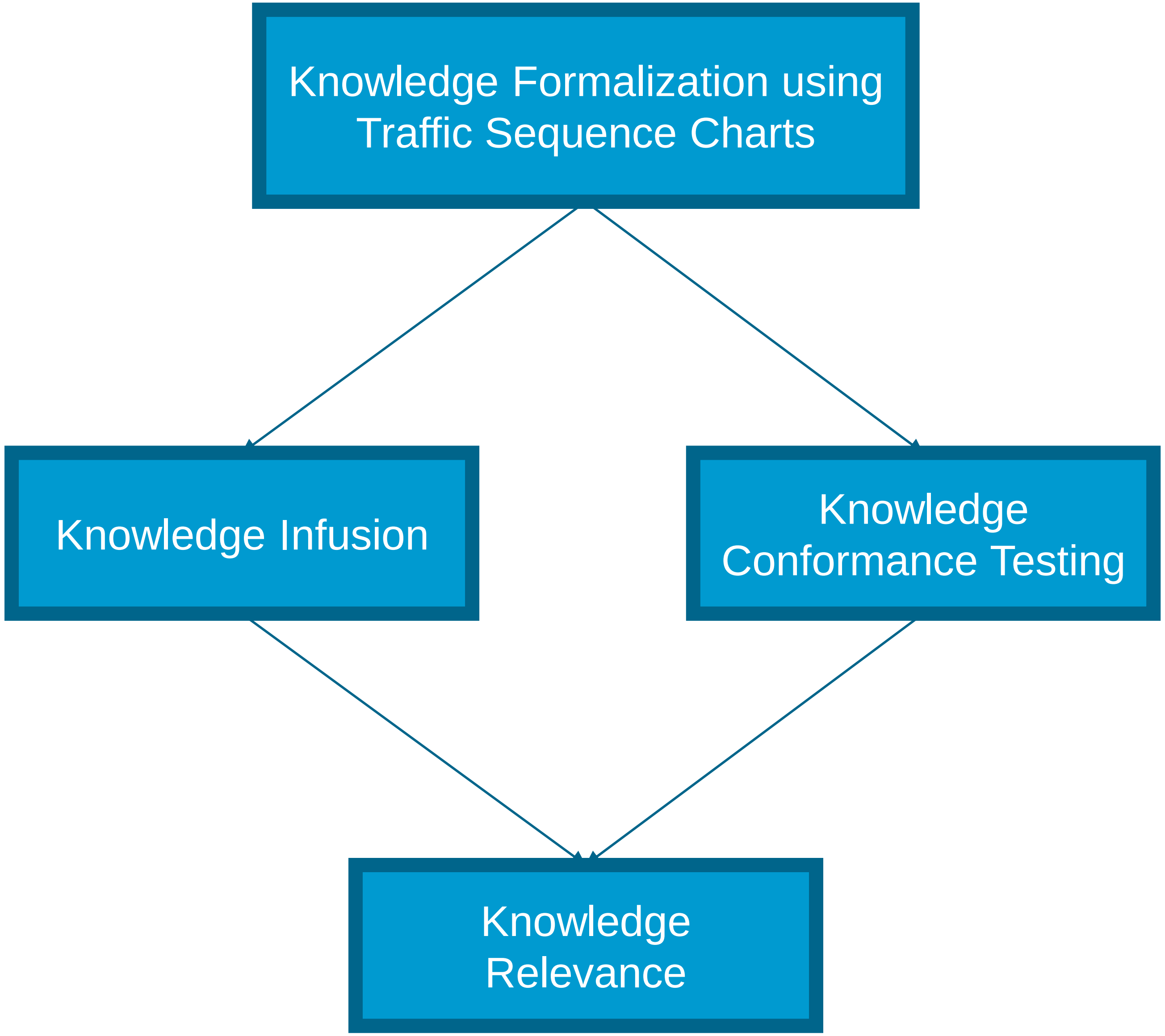
- Available knowledge from different stakeholders, e.g., lawyers, psychologists, etc.



The automated execution of essential driving maneuvers involves a shift of responsibility from the human to the system.

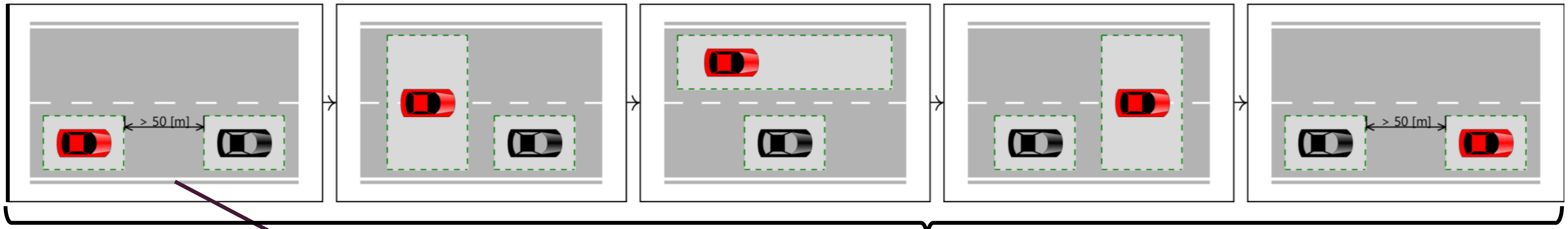
Consequently, (new) knowledge, e.g. moral aspects, social norms and normative knowledge, must be integrated into the system.

Outline


Knowledge Formalization using Traffic Sequence Charts
Knowledge Infusion
Knowledge Conformance Testing
Knowledge Relevance

Knowledge Formalization using Traffic Sequence Charts

Traffic Sequence Charts (TSC)



Spatial Properties

- Spatial Views allow to specify spatial constraints for individual maneuver phases
- For instance:
  - Distances
  - Positional relations
  - Phys. properties (velocity, etc.)

Temporal Properties

- Chart Structures allow to specify and constrain the temporal order of phases
- Sequence-Example
  - Five phases have to take place consecutively for an overtaking maneuver

Knowledge Formalization using TSC

Declarative Knowledge

Ontological Knowledge	Physical Knowledge	Script Knowledge	Deontic Knowledge	Epistemic Knowledge
A car is a vehicle.	$\dot{x} = v \cdot \cos(\theta)$ $\dot{y} = v \cdot \sin(\theta)$ $\dot{\theta} = v \cdot \frac{\tan \delta}{L}$ $\dot{v} = a$	1. Approach 2. Change Lane 3. Overtake 4. Change Lane	Max. Speed is $50 \frac{\mathrm{km}}{\mathrm{h}}$	„I sense (believe) there is a pedestrian in front of me.“
TSC: ✓	TSC: ✓	TSC: ✓	TSC: ✓	TSC: ✗

- We investigated the capabilities of Traffic Sequence Charts (TSCs) to formalize multimodal knowledge.
- We categorized relevant multimodal knowledge describing *what* (Ontology) traffic objects *should* or *must* (Script, Deontic) do under *which* (Physics) dynamic capabilities.


ego.dist_left > 250m
10m < ego.dist_right < 35m
bus.v = 0 m/s
ego.v < 2m/s
ego.dist_right > 2m
bus.v = 0 m/s
ego.v < 2m/s
ego.dist_lat > 2m
bus.v = 0 m/s
> 50 [m]
> 50 [m]
otherVehicle.v = 0
egoVehicle.v > 0
≤ 5m
egoVehicle.v > 0
cyclist.v > 0
otherVehicle.v < 0
ego.gamma = 0
obstacle.v = 0[m/s]
ego.gamma > 0
obstacle.v = 0[m/s]
or
ego.gamma > 0
obstacle.v = 0[m/s]
obstacle.v = 0[m/s]
ego_d_sensor.d_left > 1000[m]

Formalization of multi-stakeholder and multi-modal knowledge is needed.

Traffic Sequence Charts (TSCs) can be a solution for spatio-temporal knowledge.

Knowledge Formalization using Traffic Sequence Charts

Knowledge Infusion

Knowledge Infusion using TSC

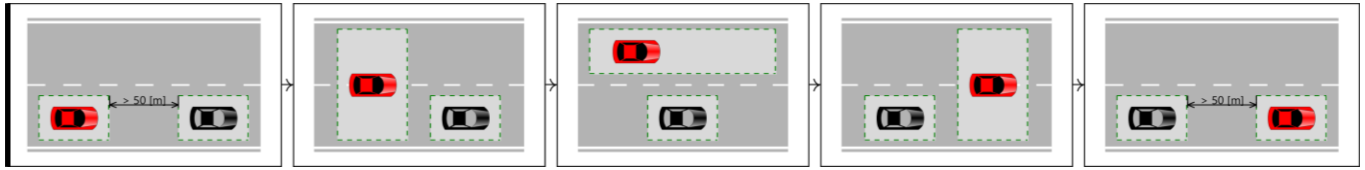
Declarative Knowledge

- Describe *what* maneuvers have to be realized.
- It is not specified on *how* to realize the maneuvers

Performative Knowledge

- RL-Agent controls vehicle through maneuvers satisfying the TSC specification
- Invariant based reward function

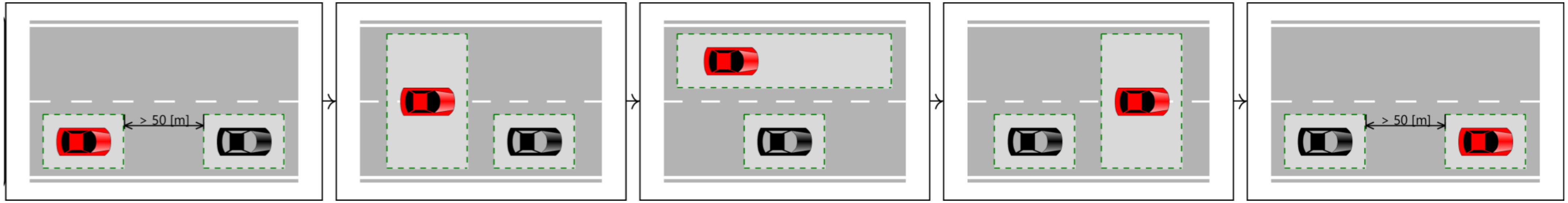
Declarative Knowledge



TSC
2RL

Performative Knowledge

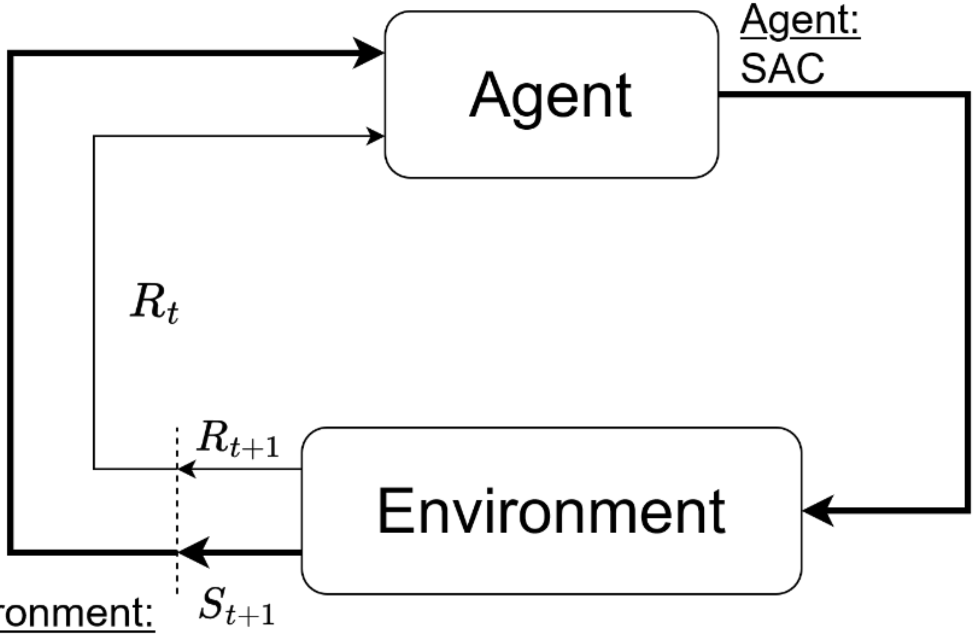
TSC2RL Training Environment



Epistemic Knowledge

<u>Observation Space</u>
- θ_{ego}: Heading
- v_{ego}: Velocity
- Observable distances from **TSC constraints**

Script Knowledge



<u>Agent:</u>
SAC

<u>Action:</u>
a_{ego}: Acceleration
δ_{ego}: Steering

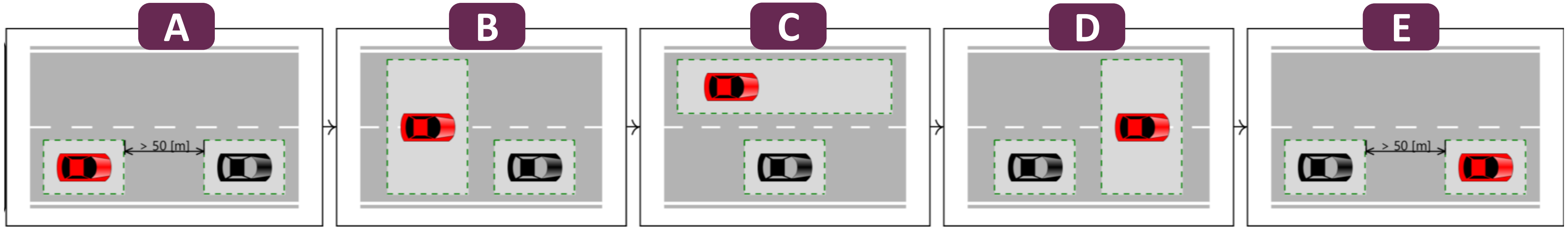
Deontic Knowledge

Physical Knowledge

<u>Environment:</u>
Vehicles Ego and $Other$ on a $Road$ with two $Lanes$. (**TSC objects**)
Ego is modeled with Bicycle Model. (**Physical Knowledge**)

Ontological Knowledge

TSC2RL – Reward Function



A: $y_{ego} < 0$, $-y_{ego} < 4$, $x_{ego} - x_{other} < 50$

B: $y_{ego} < 4$, $-y_{ego} < 4$, $x_{ego} - x_{other} < 0$

C: $y_{ego} < 4$, $-y_{ego} < 0$

D: $y_{ego} < 4$, $-y_{ego} < 4$, $x_{other} - x_{ego} < 0$

E: $y_{ego} < 0$, $-y_{ego} < 4$, $x_{other} - x_{ego} < 50$

Reward Function

- Ego has to follow the overtaking TSC
- The agent has to select appropriate actions such that the TSC invariants $A, \dots, E$ are satisfied in correct order
- Satisfaction is checked and reward is given according to progress

$$
\begin{aligned}
\varphi_A &\coloneqq x_{ego} - x_{other} < 50 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 0 \\
\varphi_B &\coloneqq x_{ego} - x_{other} < 0 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 4 \\
\varphi_C &\coloneqq -y_{ego} < 4 \;\wedge\; y_{ego} < 4 \\
\varphi_D &\coloneqq x_{other} - x_{ego} < 0 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 4 \\
\varphi_E &\coloneqq x_{other} - x_{ego} < 50 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 0
\end{aligned}
$$

$$
R = \begin{cases}
1 & \text{if } \varphi_E, \\
0.75 & \text{if } \varphi_D \wedge \neg\varphi_E, \\
0.5 & \text{if } \varphi_C \wedge \neg\varphi_D \wedge \neg\varphi_E, \\
0.25 & \text{if } \varphi_B \wedge \neg\varphi_C \wedge \neg\varphi_D \wedge \neg\varphi_E, \\
0 & \text{if } \varphi_A \wedge \neg\varphi_B \wedge \neg\varphi_C \wedge \neg\varphi_D \wedge \neg\varphi_E, \\
-1 & \text{otherwise.}
\end{cases}
$$

TSC2RL – Trained Agents

Training

- $x_{ego} \in [0m, 50m]$, $x_{other} = 100m$
- $v_{other} = 0\frac{\mathrm{m}}{\mathrm{s}}$
- 500.000 steps á $dt = 0.02s$
- Episodes of 40s

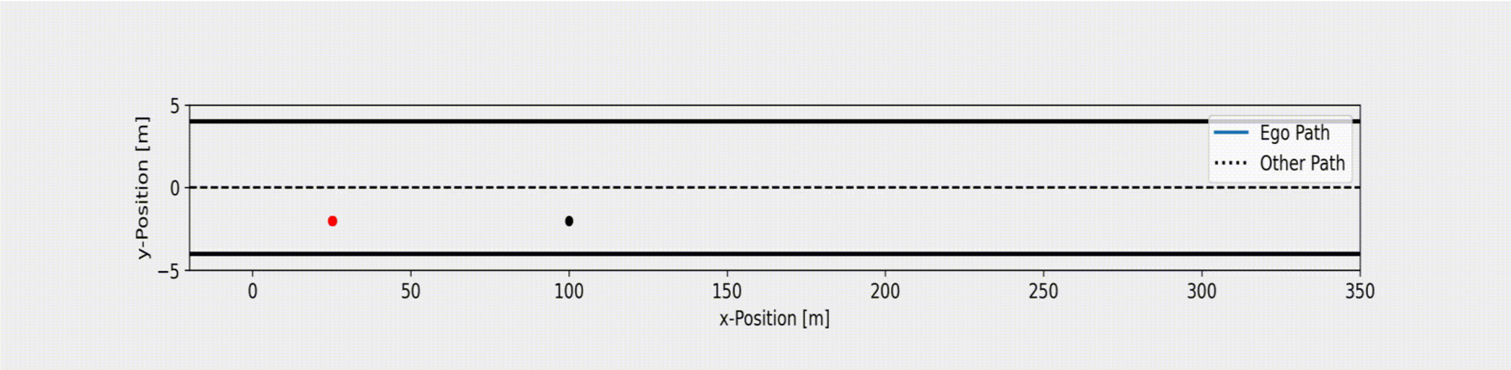
Application

- Training Condition: $v_{other} = 0\frac{m}{s}$
- Transfer (without training again): $v_{other} = 10\frac{m}{s}$

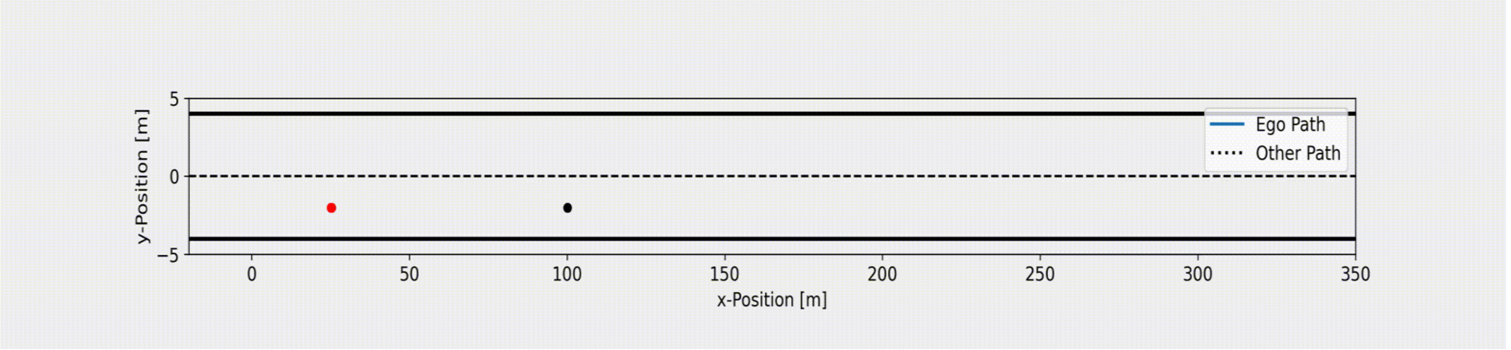
Results

- Each agent realize to overtake
- Even for $v_{other} \neq 0\frac{m}{s}$ without additional training

$v_{other} = 0\frac{\mathrm{m}}{\mathrm{s}}$



$v_{other} = 10\frac{\mathrm{m}}{\mathrm{s}}$



Knowledge-infusion may increase performance, safety and trustworthiness.

TSC Reinforcement Learning can be a solution for infusing spatio-temporal knowledge.

“Using Traffic Sequence Charts for Knowledge Formalization and AI-Application”

Intelligent Systems and Application (Proceedings of IntelliSys 2024) Springer LNCS (2024)

Using Traffic Sequence Charts for Knowledge Formalization and AI-Application

Philipp Borchers[1], Willem Hagemann[2], Dominik Grundt[1], Tino Werner[1], and Julian Müller[1]

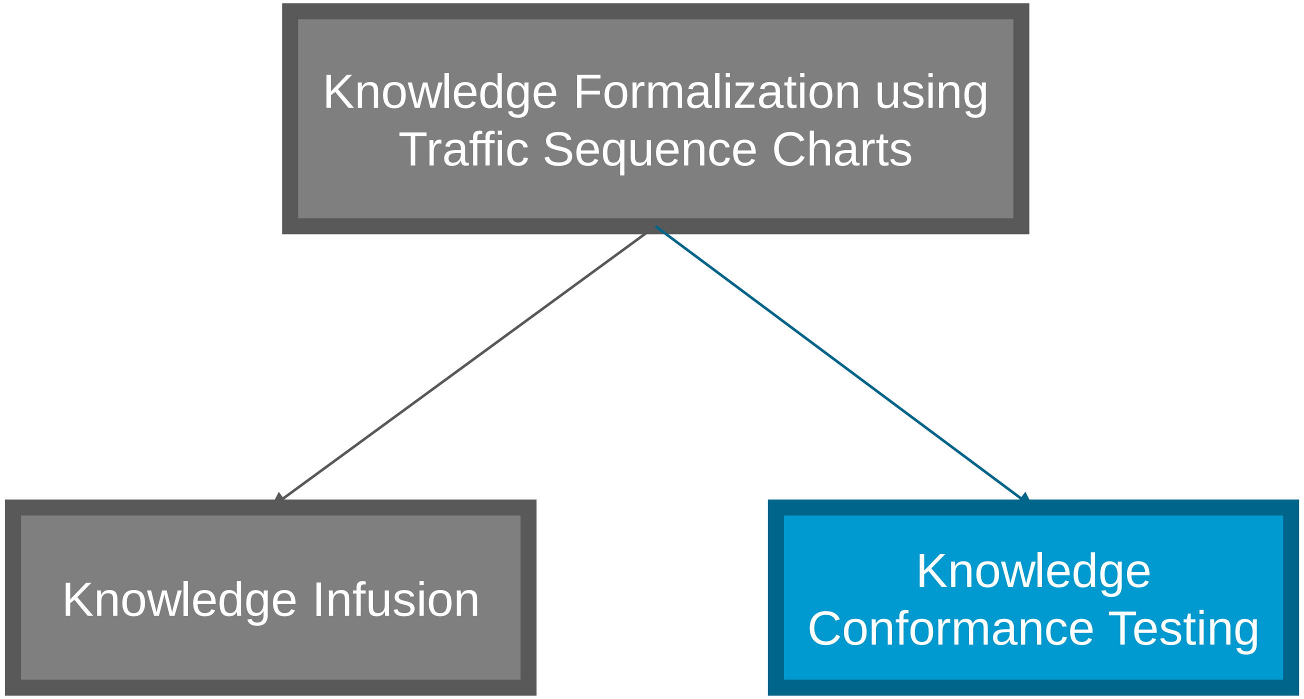
[1] German Aerospace Center (DLR)
Institute of Systems Engineering for Future Mobility
Escherweg 2, 26129 Oldenburg, Germany
philipp.borchers@dlr.de

[2] Fraunhofer Research Institution for Energy Infrastructures and Geothermal Systems IEG
Gulbener Straße 23, 03046 Cottbus

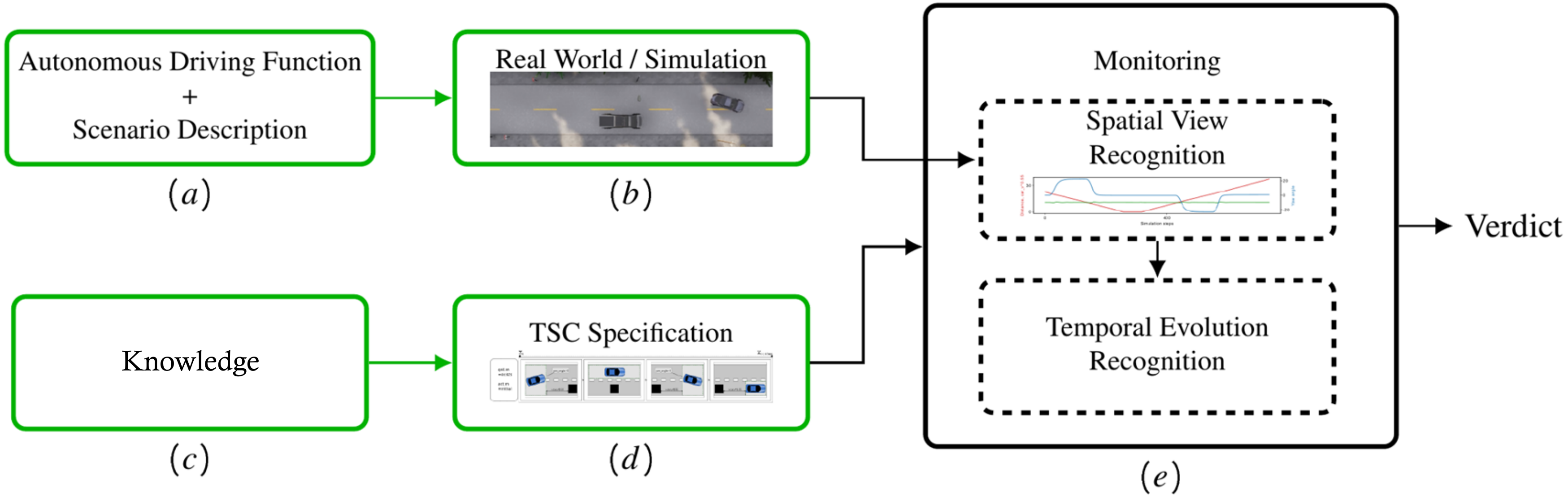
Abstract. In recent years, the integration of knowledge into AI training processes has been shown as a promising approach to improve AI performance, training costs and resource efficiency. Here, the formalization of knowledge is a key challenge. In this article, we discuss the capabilities of the visual yet formal specification language called Traffic Sequence Charts (TSC) on formalizing multimodal knowledge, in particular procedural knowledge about traffic maneuvers. Finally, we present an approach using the formalized knowledge to train reinforcement learning (RL) agents, aiming to transform the descriptive knowledge on traffic maneuvers in TSCs into performative knowledge in AI traffic agents. To this end, we were able to train an agent to control a vehicle through a pass-by maneuver and apply it successfully to an untrained overtaking maneuver.

Keywords: Knowledge Formalization, Reinforcement Learning, Traffic Scenarios, Abstract Scenario Specification

This research was partly funded by the German Federal Ministry of Economic Affairs and Climate Action (BMWK) through the ”KI Wissen” project under grant agreement No. 19A20020M.

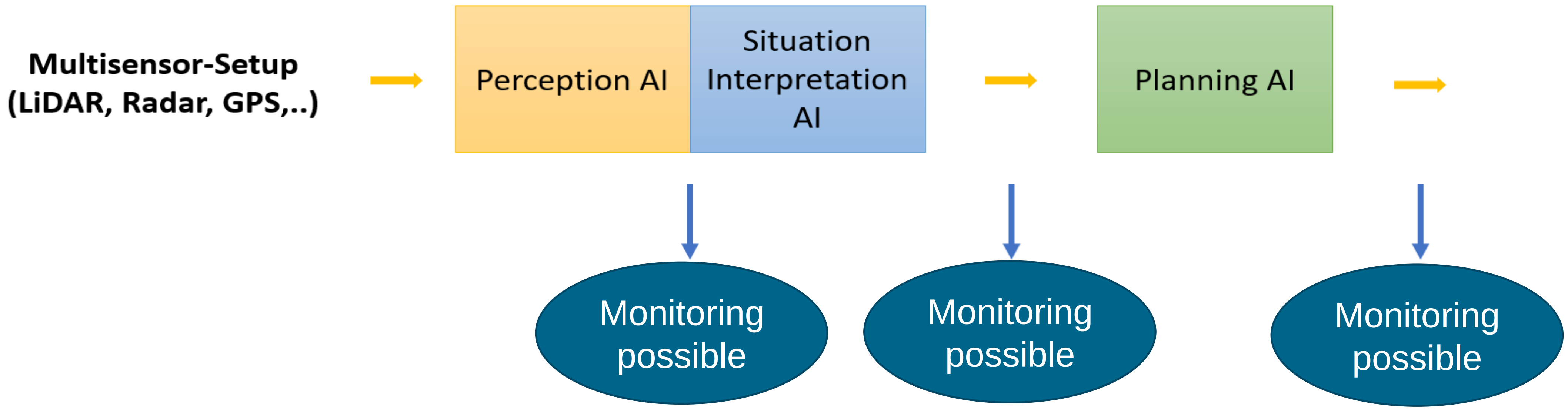

Knowledge Formalization using Traffic Sequence Charts
Knowledge Infusion
Knowledge Conformance Testing

TSC Online Monitoring



- Continuous verdicts about Traffic Sequence Charts (TSCs) compliance during runtime
- Exploiting the structure of TSC formalism
- Separation of concerns w.r.t
  - Spatial properties: Spatial View Recognition (SVR)
  - Temporal properties: Temporal Evolution Recognition (TER)
  - Monitor provides verdict: satisfied, violated or inconclusive

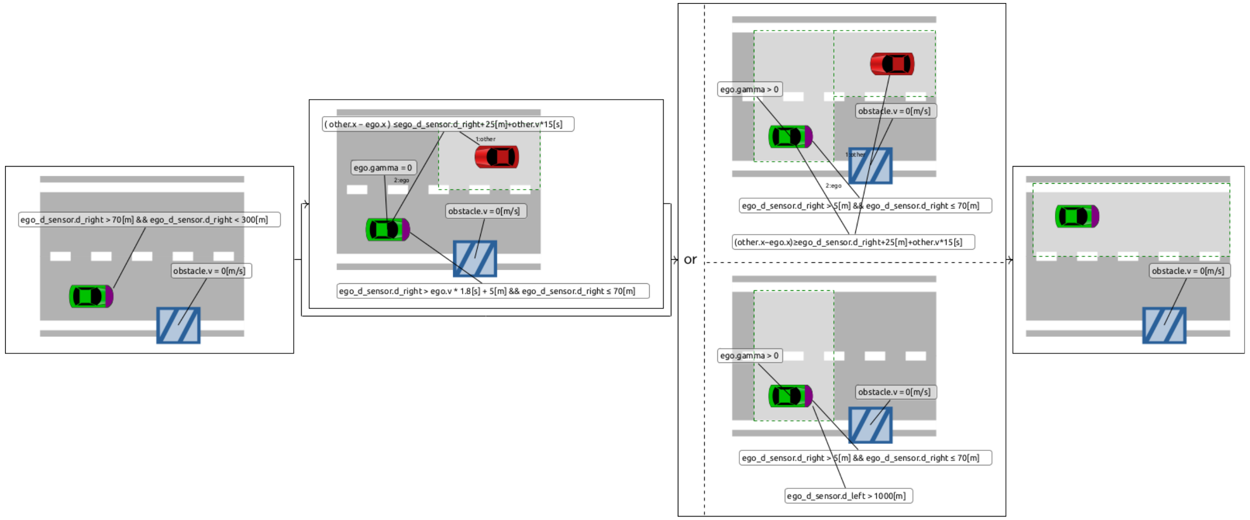
Interfaces for AI Online Monitoring

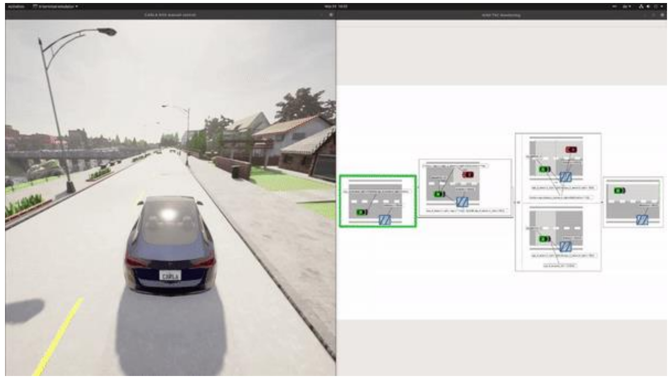


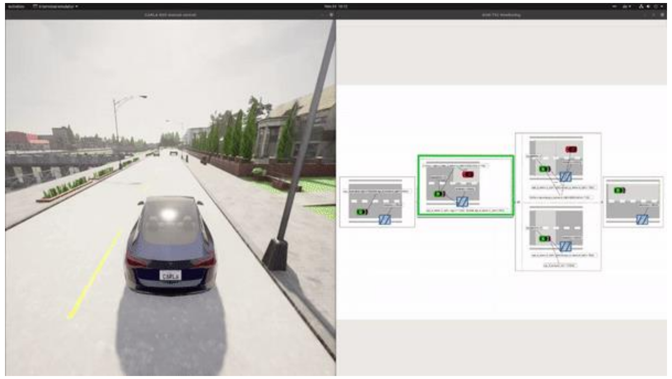
Online Monitoring – Pass-By Maneuver

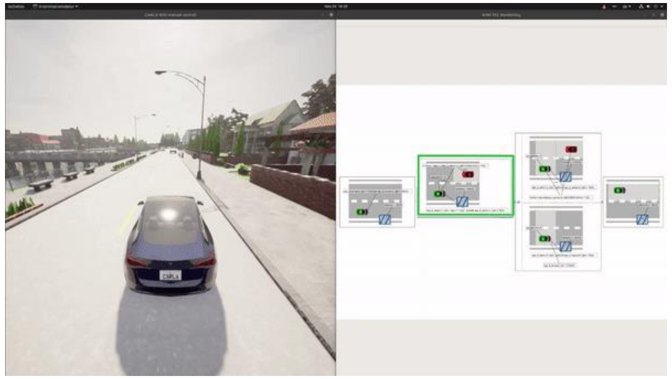
„We want to monitor, if the decision to start passing-by the obstacle is correct.“

- Physical knowledge
- Deontic knowledge









Testing knowledge conformance at runtime increases the efficiency of training and testing.

For this, TSC Online Monitoring utilizes TSC knowledge formalization.

DLR

"Towards Runtime Monitoring of Complex System Requirements for Autonomous Driving Functions"

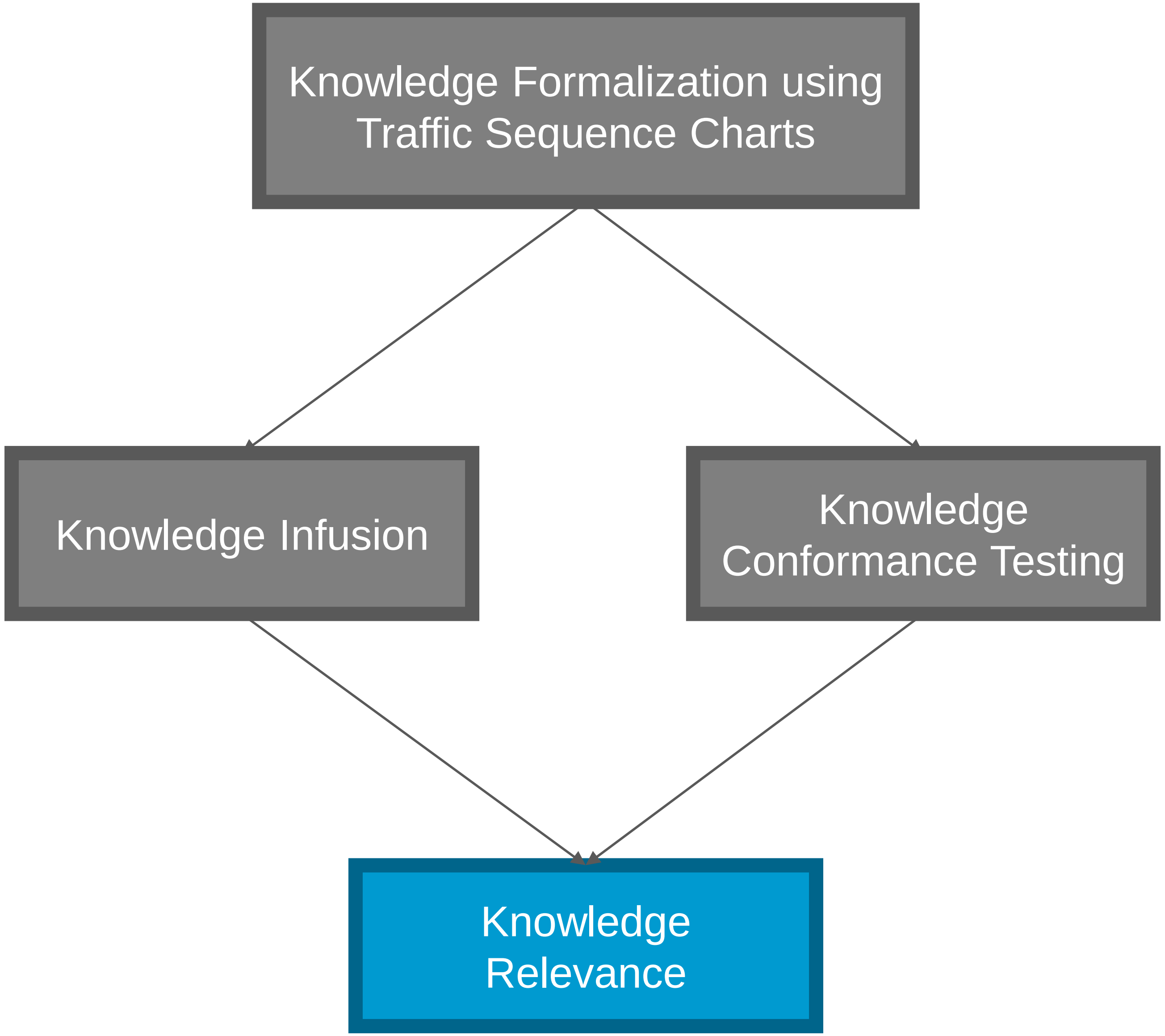
Proceedings 4th International Workshop on Formal Methods for Autonomous Systems, EPTCS, Vol. 371 (2022)

Towards Runtime Monitoring of Complex System Requirements for Autonomous Driving Functions*

Dominik Grundt dominik.grundt@dlr.de
Anna Köhne anna.koehne@dlr.de
Ishan Saxena ishan.saxena@dlr.de
Ralf Stemmer ralf.stemmer@dlr.de
Bernd Westphal bernd.westphal@dlr.de
Eike Möhlmann eike.moehlmann@dlr.de

German Aerospace Center
Institute of Systems Engineering for Future Mobility
Oldenburg, Germany

Autonomous driving functions (ADFs) in public traffic have to comply with complex system requirements that are based on knowledge of experts from different disciplines, e.g., lawyers, safety experts, psychologists. In this paper, we present a research preview regarding the validation of ADFs with respect to such requirements. We investigate the suitability of Traffic Sequence Charts (TSCs) for the formalization of such requirements and present a concept for monitoring system compliance during validation runs. We find TSCs, with their intuitive visual syntax over symbols from the traffic domain, to be a promising choice for the collaborative formalization of such requirements. For an example TSC, we describe the construction of a runtime monitor according to our novel concept that exploits the separation of spatial and temporal aspects in TSCs, and successfully apply the monitor on exemplary runs. The monitor continuously provides verdicts at runtime, which is particularly beneficial in ADF validation, where validation runs are expensive. The next open research questions concern the generalization of our monitor construction, the identification of the limits of TSC monitorability, and the investigation of the monitor's performance in practical applications. Perspectively, TSC runtime monitoring could provide a useful technique in other emerging application areas such as AI training, safeguarding ADFs during operation, and gathering meaningful traffic data in the field.

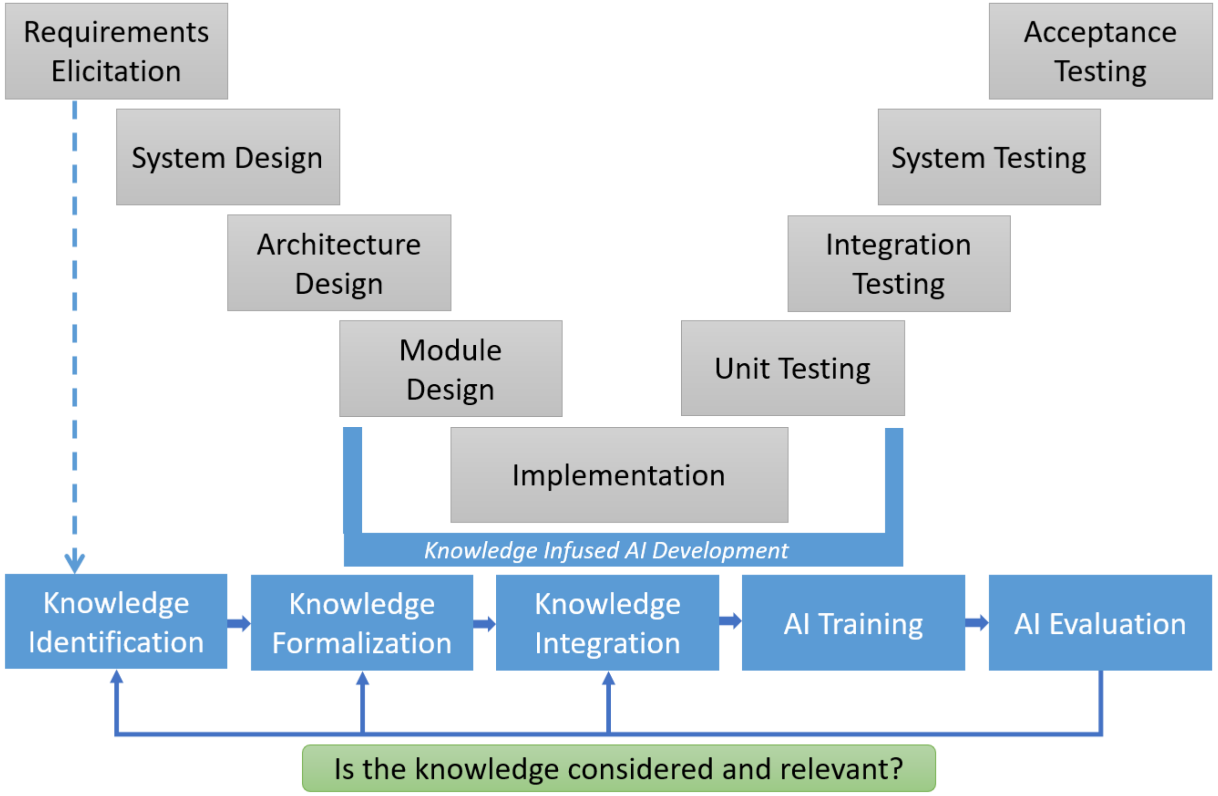

Knowledge Formalization using Traffic Sequence Charts
Knowledge Infusion
Knowledge Conformance Testing
Knowledge Relevance

Knowledge Relevance

- Assessing knowledge relevance enables the
  - development of a knowledge base for new AI driving functions, and
  - implementation of new - and verification of exisiting AI explanations

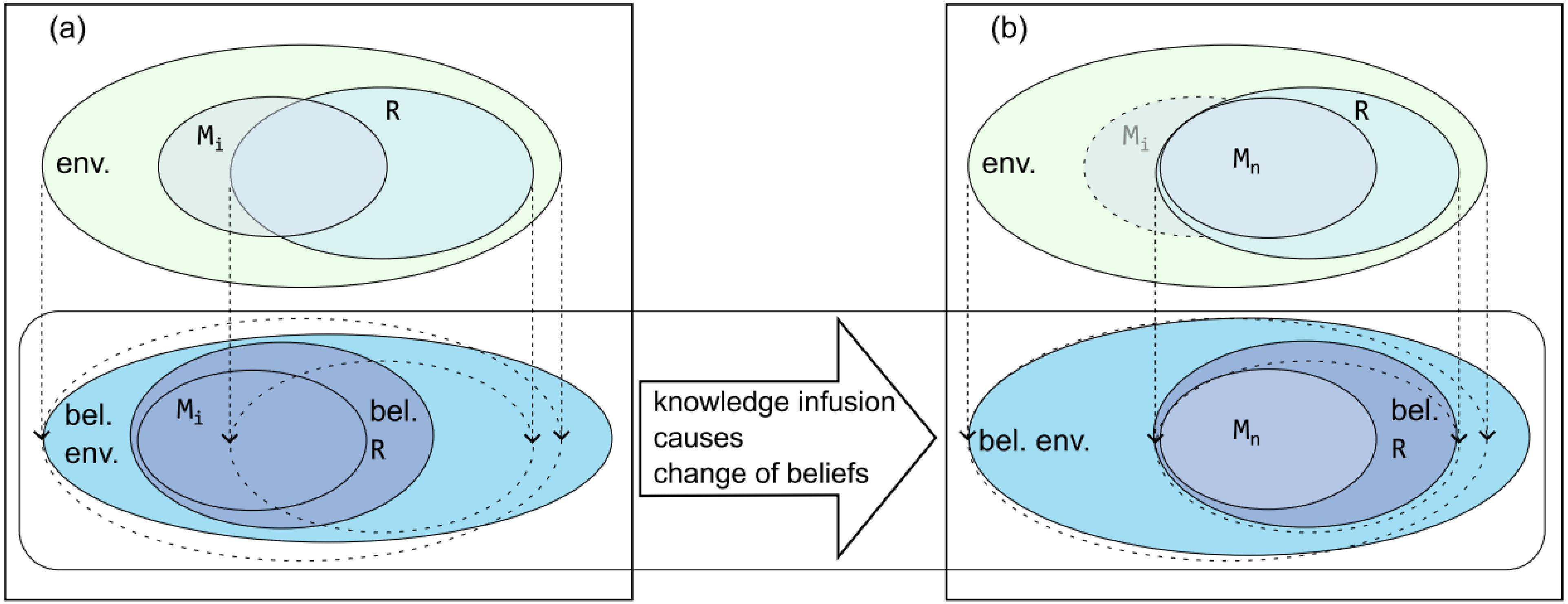
- Requirements-driven development process

- Goal: Knowledge-infused AI satisfies top-level requirements



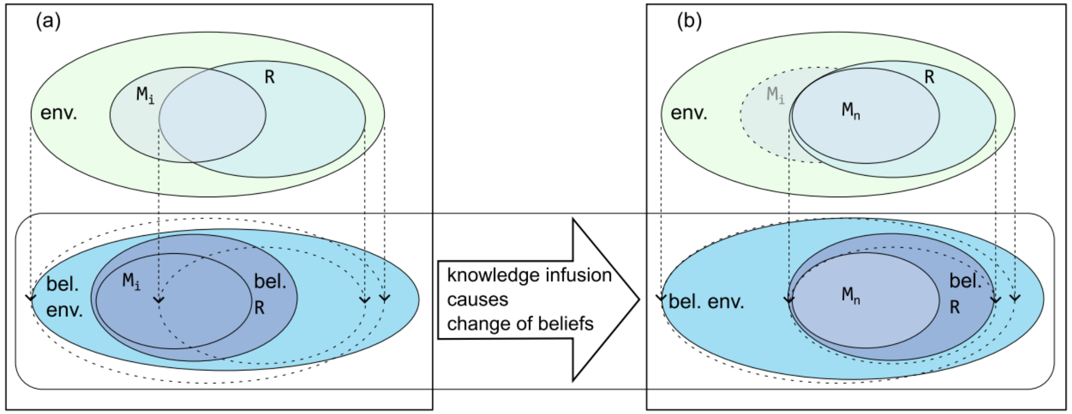
Knowledge Infusion Operation (KIO)

- Setup: An exisiting model M_i is not satisfying its requirements R
- Task: Infuse knowledge, that enables M_i to satisfy its requirements
- Concrete: Change of M_i's beliefs or internal world model



Knowledge Infusion Operation (KIO)

- Setup: An exisiting model M_i is not satisfying its requirements
- Task: Infuse knowledge, that enables M_i to satisfy its requirements
- Concrete: Change of M_i's beliefs or internal world model



- Given an initial model M_i, knowledge K, means of integration I (architecture or knowledge as input), and a training process P_t
- KIO $\odot$ yields a new model: $M_n = \odot\,(M_i, K, I, P_t)$

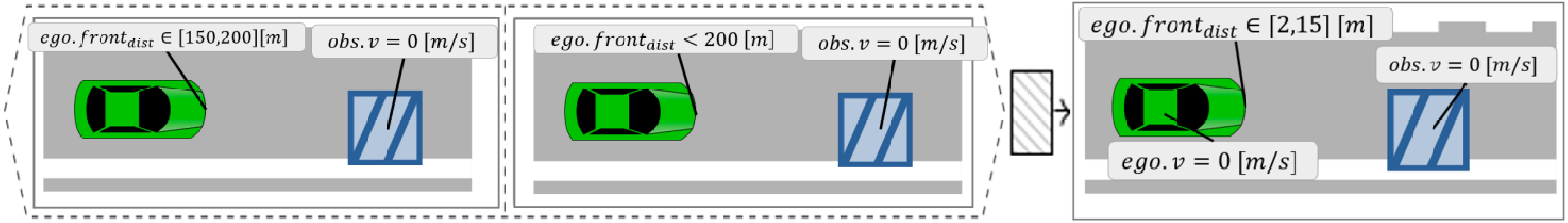
Notion of Relevance - Knowledge-infused AI Driving Func.

- Notion of *Scenario-relevance*
  - Relation between a requirement R, a model M_i, knowledge K, a scenario $Scen$, and a test suite S
  - We say that we have an *indication* that knowledge K is relevant for M_i to satisfy R in $Scen$, if
    - M_i does not satisfy R in $Scen$ (verified by testing)
    - We can infuse K into M_i (finding I and P_t and apply $\odot$), s.t.
    - $M_n = \odot(M_i, K, I, P_t)$ satisfies R in $Scen$ (verified by testing)

© DALL-E3 (generated by AI)

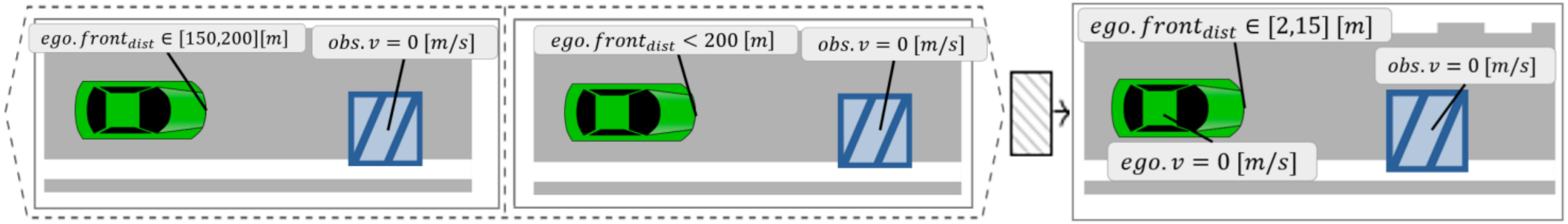
Requirement Specification using TSCs

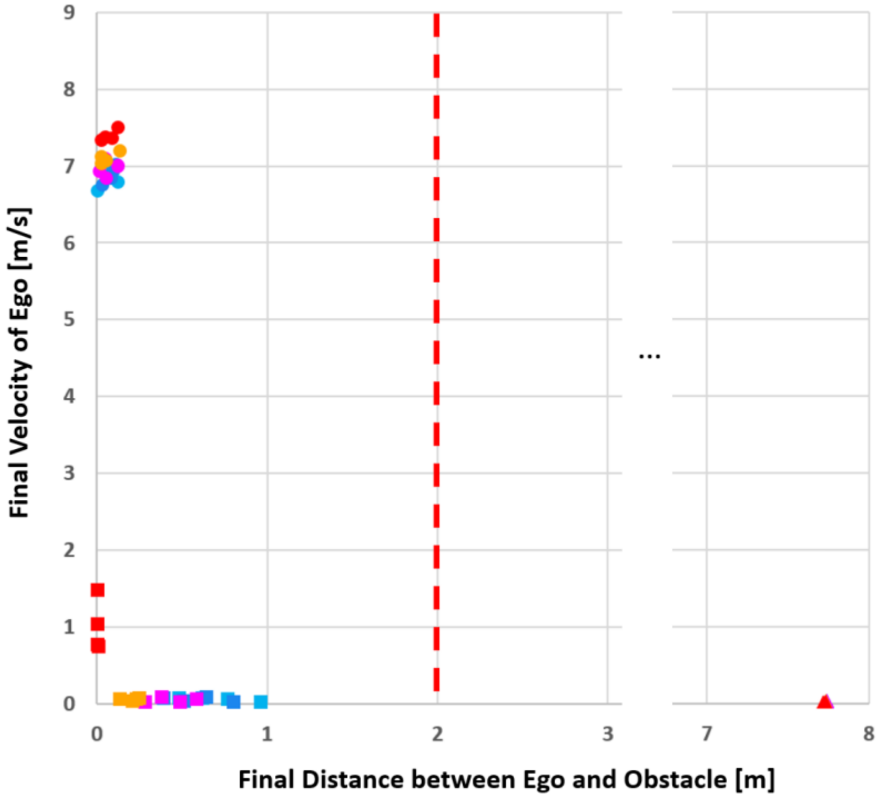
"Always stop at a distance between 2-15 meters to a static obstacle."



M_i violating requirement R due to not considering Friction

"Always stop at a distance between 2-15 meters to a static obstacle."

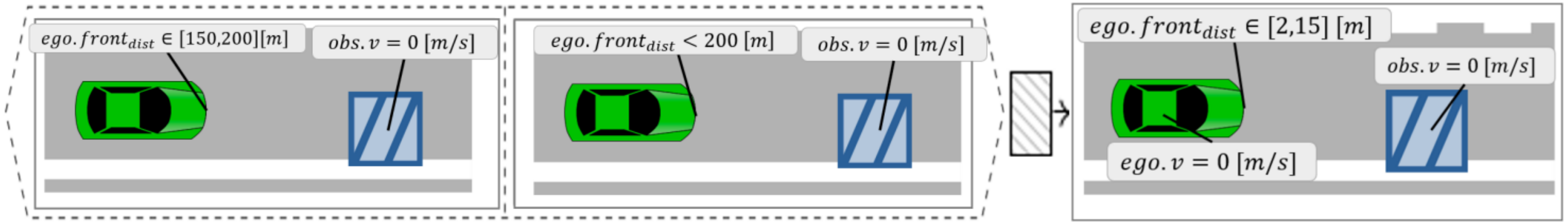




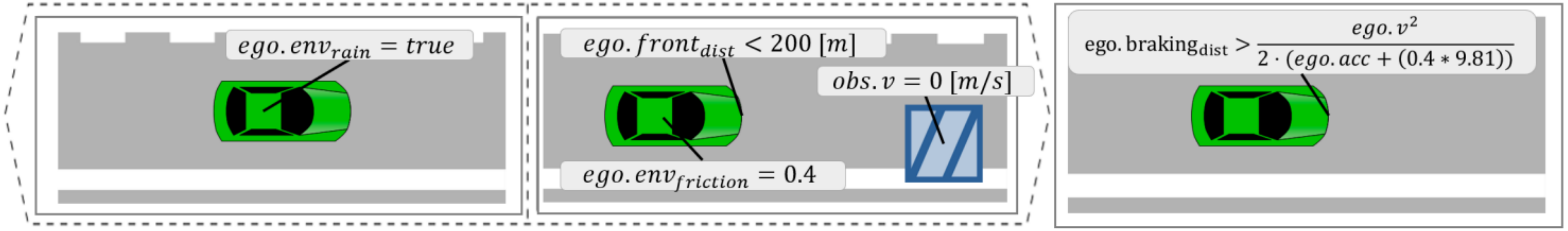
v_{ego}^0 [m/s]	Fric Coef.	Symb.
10	0.2	●
15	0.2	●
20	0.2	●
25	0.2	●
30	0.2	●
10	0.4	■
15	0.4	■
20	0.4	■
25	0.4	■
30	0.4	■
10	0.8	▲
15	0.8	▲
20	0.8	▲
25	0.8	▲
30	0.8	▲

Speci. Requirement and related Knowledge using TSCs

"Always stop at a distance between 2-15 meters to a static obstacle."

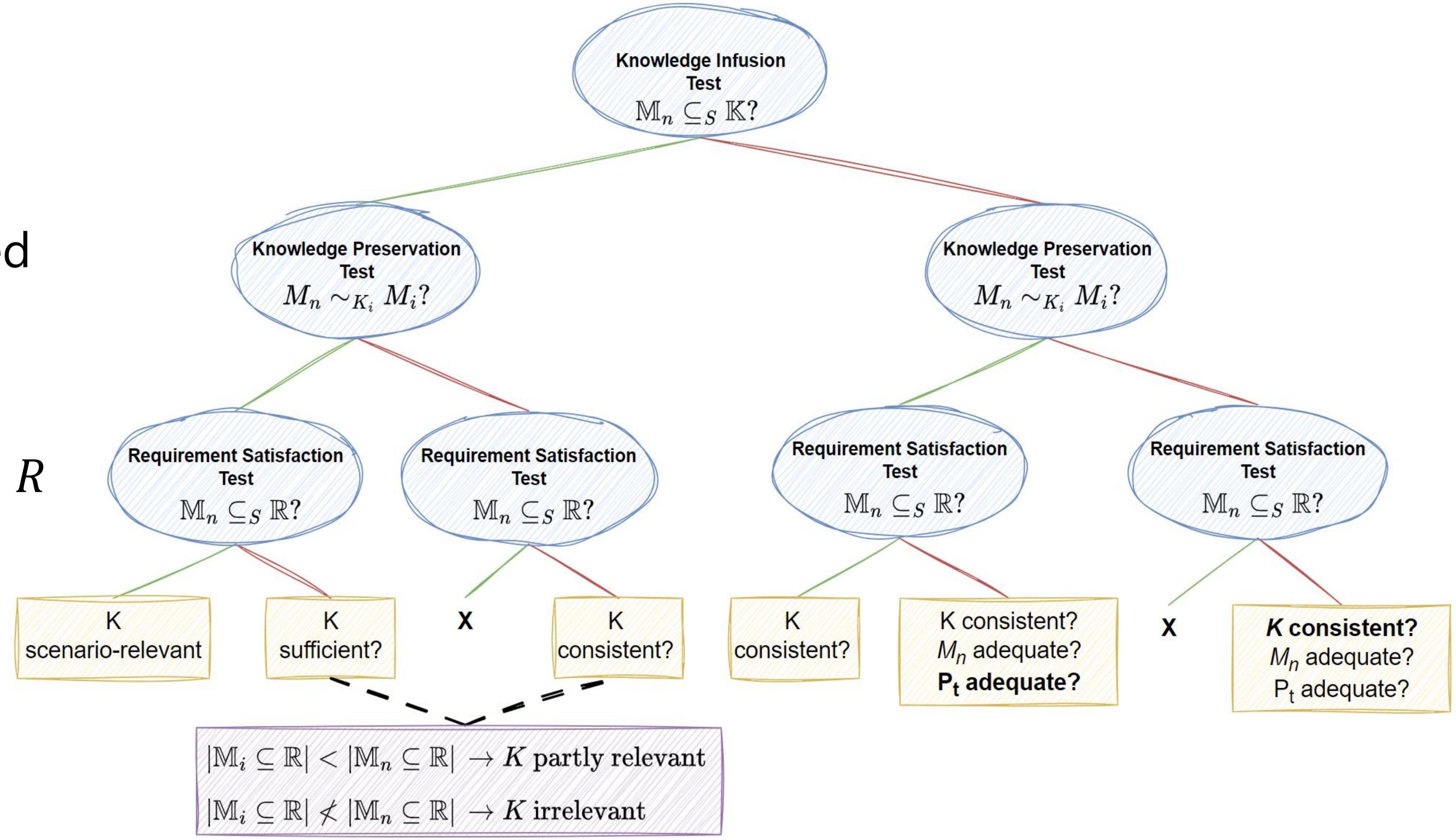


"Always if it is rainy and the friction is then reduced, brake taking the reduced friction into account."

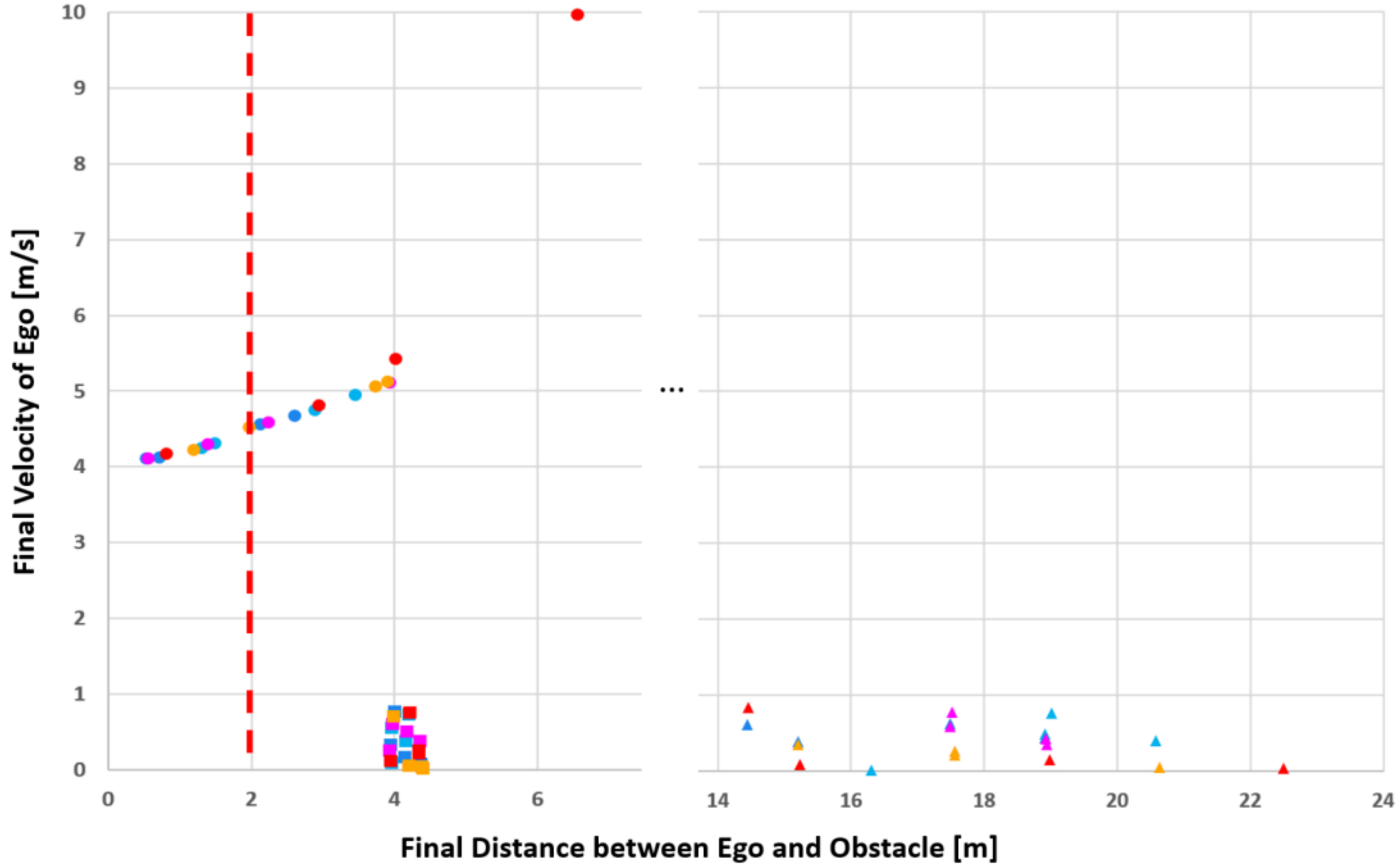


Relevance Testing Procedure

- Knowledge Infusion Test:
  - Is K infused into M_n
- Knowledge Preservation Test:
  - Is the success of M_i preserved
- Requirement Satisfaction Test:
  - Does M_n satisfy requirement R

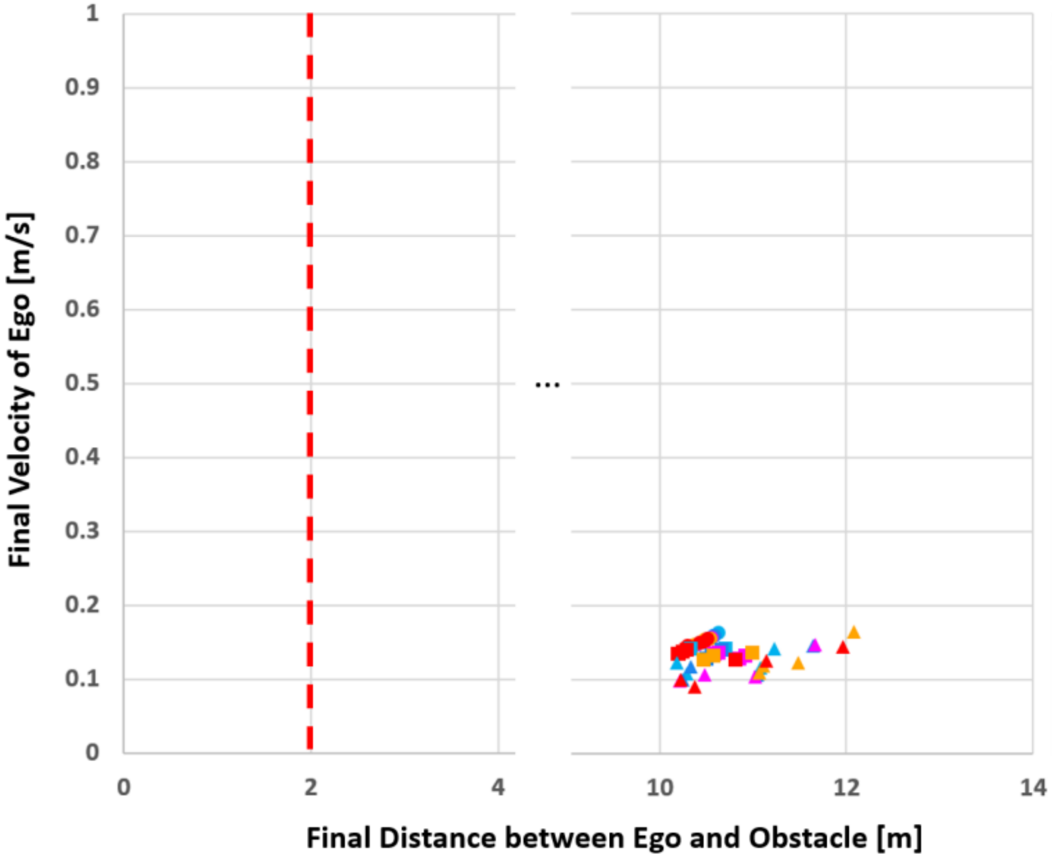


M_n violates requirement R ($|\mathbb{M}_i \subseteq \mathbb{R}| < |\mathbb{M}_n \subseteq \mathbb{R}|$)



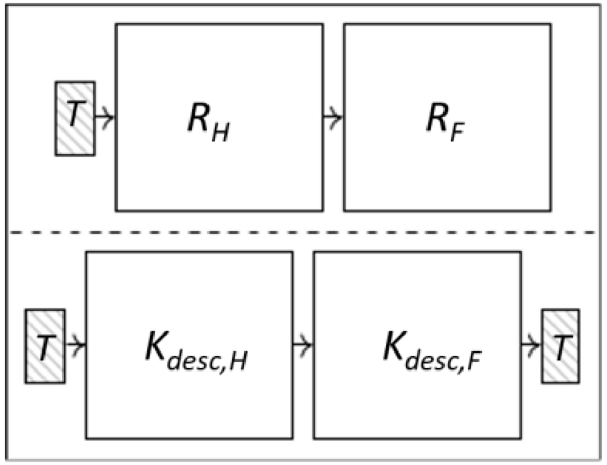
v^0_{ego} [m/s]	Fric Coef.	Symb.
10	0.2	●
15	0.2	●
20	0.2	●
25	0.2	●
30	0.2	●
10	0.4	■
15	0.4	■
20	0.4	■
25	0.4	■
30	0.4	■
10	0.8	▲
15	0.8	▲
20	0.8	▲
25	0.8	▲
30	0.8	▲

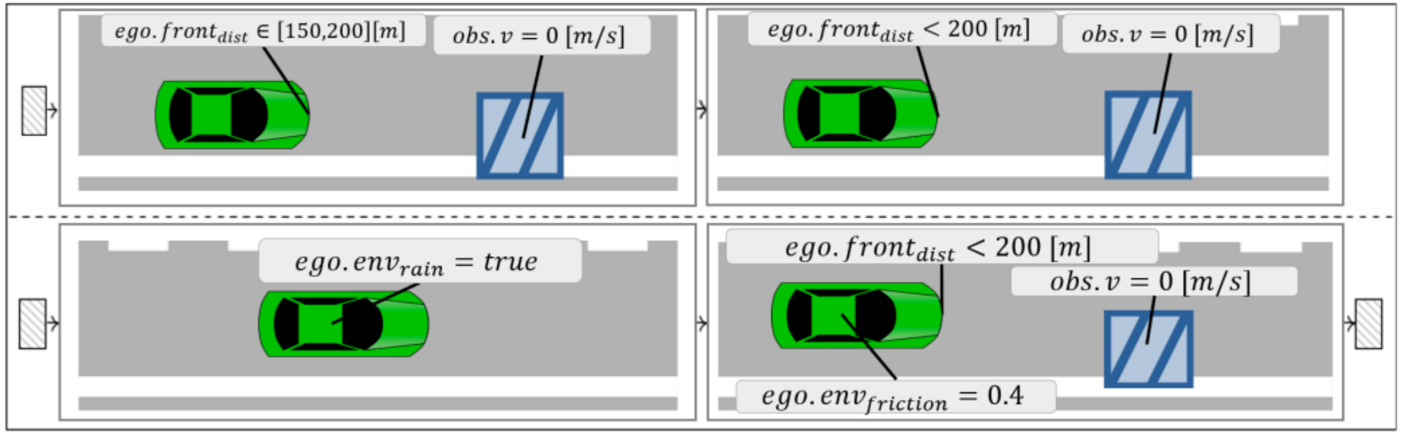
M_n satisfies requirement R (Indic. for Scenario-relevance)

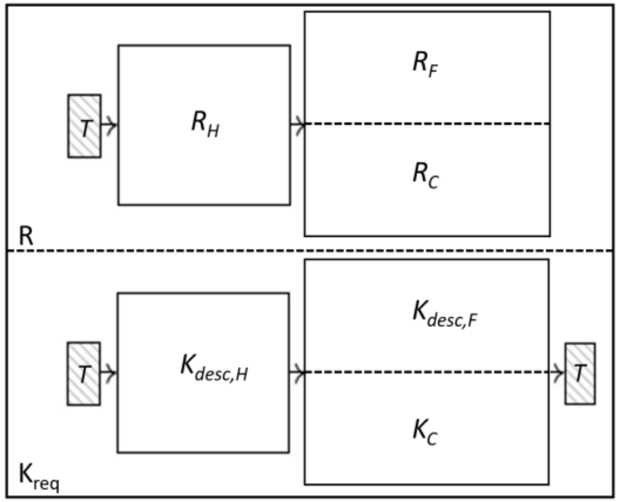


v_{ego}^0 [m/s]	Fric Coef.	Symb.
10	0.2	●
15	0.2	●
20	0.2	●
25	0.2	●
30	0.2	●
10	0.4	■
15	0.4	■
20	0.4	■
25	0.4	■
30	0.4	■
10	0.8	▲
15	0.8	▲
20	0.8	▲
25	0.8	▲
30	0.8	▲

Composed TSCs for Training and Test Instruction







New notions enable the ability of providing indications about knowledge relevance.

TSC Relevance Testing supports creating knowledge bases and explainable AI driving functions.

"What does AI Need to Know to Drive: Testing Relevance of Knowledge"

Submitted to: Special Issue "Advances in Formal Methods for Autonomous Systems",
Journal: Science of Computer Programming

What does AI Need to Know to Drive: Testing Relevance of Knowledge

Dominik Grundt, Astrid Rakow, Philipp Borchers, Eike Möhlmann

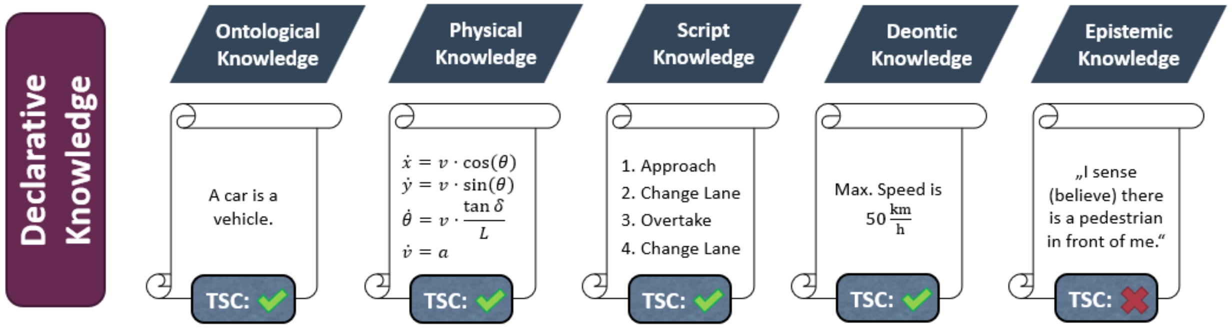
German Aerospace Center e.V. - Institute of Systems Engineering for Future Mobility
Oldenburg, Germany

Abstract

Artificial Intelligence (AI) plays an important role in managing the complexity of automated driving. Nonetheless, training and ensuring the safety of AI is challenging. The safe generalization from a known to an unknown situation remains an unsolved problem. Infusing knowledge into AI driving functions seems a promising approach to address generalization, development costs, and training efficiency. Ascertaining the relevance of infused knowledge provides a strong indication of the correct execution of previous development phases (e.g., identification and formalization). As a causal reason for AI performance, relevant knowledge is important for explaining AI behavior. This paper defines a novel notion of *relevant knowledge* in knowledge-infused AI and for requirements satisfaction in traffic scenarios. Furthermore, we present a testing procedure for scenario-based development, which provides statements on the relevance of infused knowledge. Finally, we describe a systematic method for generating abstract knowledge scenarios to enable an efficient application of our relevance testing procedure.

Keywords: Knowledge-infused AI, Relevance, AI driving functions

Summary



$$
\begin{aligned}
\varphi_A &:= x_{ego} - x_{other} < 50 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 0\\
\varphi_B &:= x_{ego} - x_{other} < 0 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 4\\
\varphi_C &:= \quad -y_{ego} < 4 \;\wedge\; y_{ego} < 4\\
\varphi_D &:= x_{other} - x_{ego} < 0 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 4\\
\varphi_E &:= x_{other} - x_{ego} < 50 \;\wedge\; -y_{ego} < 4 \;\wedge\; y_{ego} < 0
\end{aligned}
$$

$$
R = \begin{cases}
1 & \text{if } \varphi_E,\\
0.75 & \text{if } \varphi_D \wedge \neg\varphi_E,\\
0.5 & \text{if } \varphi_C \wedge \neg\varphi_D \wedge \neg\varphi_E,\\
0.25 & \text{if } \varphi_B \wedge \neg\varphi_C \wedge \neg\varphi_D \wedge \neg\varphi_E,\\
0 & \text{if } \varphi_A \wedge \neg\varphi_B \wedge \neg\varphi_C \wedge \neg\varphi_D \wedge \neg\varphi_E,\\
-1 & \text{otherwise.}
\end{cases}
$$