KI WISSEN
Automotive AI Powered by Knowledge

2.6 Integration of a Priori Knowledge Using a Causal Model of Vehicle Trajectories

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Trajectory Prediction and Motion Planning

Data Augmentation Using Causal Models

Automated driving functions based on machine learning (ML) face the challenge of reacting robustly to scenarios that are scarce in the training data. In principle, causal models allow us to reason about queries on all three levels of the *Causal Hierarchy* (cf. Table 1). We use these queries to generate new samples for augmenting the training data for ML functions. Figure 1 shows a counterfactual trajectory generated by our causal model.

Level	Example query
1. Association (seeing / observing)	*What is the most likely sequence of actions given we observed a particular trajectory?*
2. Intervention (doing)	*What will happen if the driver applies a particular sequence of actions moving forward?*
3. Counterfactual (imagining)	*What would have happened if the vehicle's longitudinal acceleration had been 1 m/s² higher than it was?*

Table 1: Example queries on the three levels of the Causal Hierarchy.

A Causal Model of Vehicle Trajectories

We formalize knowledge about the generative process of vehicle trajectories in terms of a Structural Causal Model (SCM) (cf. Figure 2). The generative model maps state-action pairs (s_t, a_t) of the vehicle onto the next state s_{t+1} via the physical dynamics model M. The guide provides a posterior approximation of the state-action pairs $(\hat{s}_t, \hat{a}_t)$ at every timestep, conditioned on the full sequence of observations o_t, using the hidden recurrent states h_t. All neural networks in the SCM are trained conjointly on vehicle trajectory data.

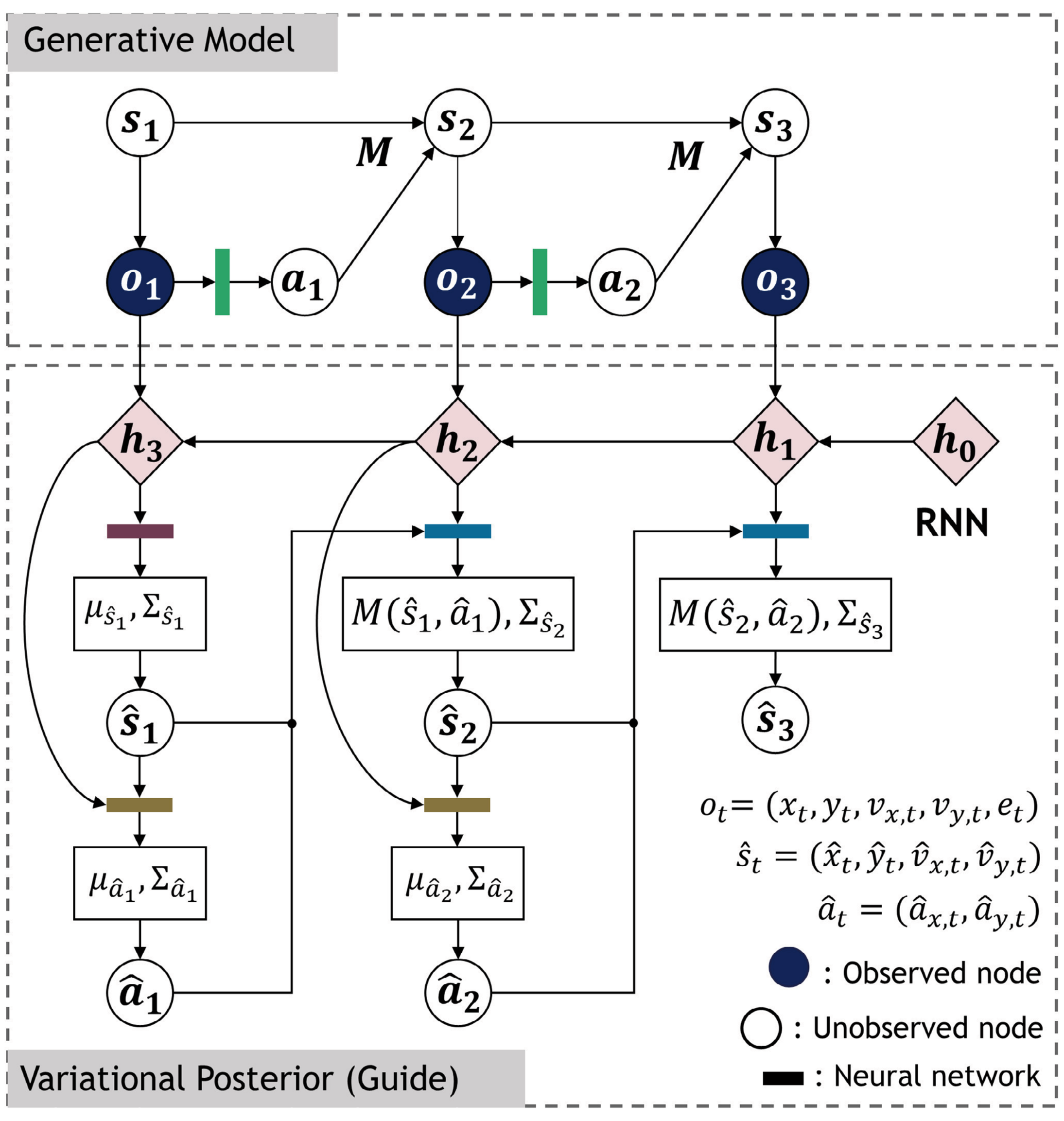

Figure 2: Schematic representation of our causal model for vehicle trajectories. (© e:fs TechHub GmbH, adapted from [1])

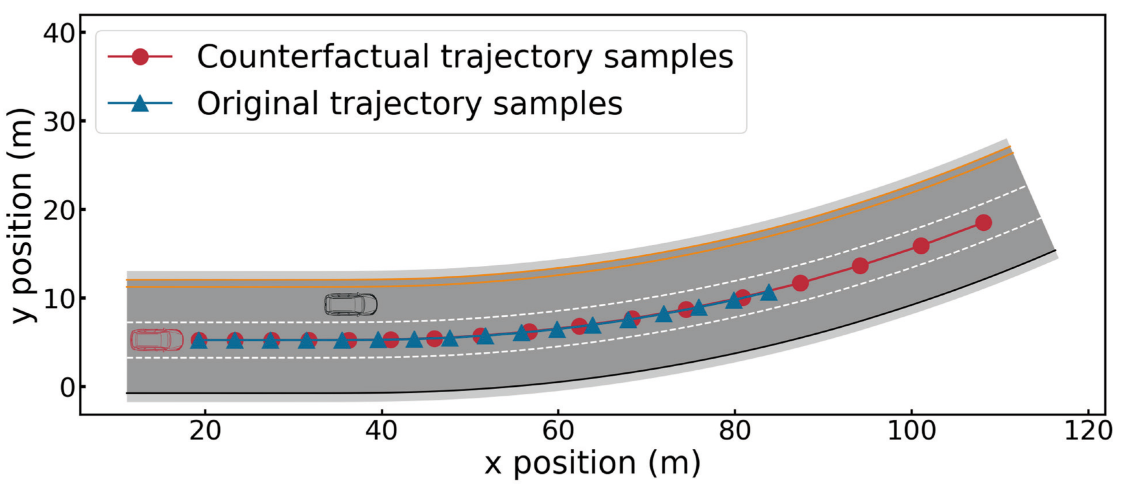

Figure 1: Example for answering the counterfactual query: what would have happened if the vehicle's longitudinal acceleration had been 1 m/s² higher than it was? (© e:fs TechHub GmbH)

Knowledge Integration into Model-based RL

We adopt a model-based reinforcement learning (RL) agent and embed our SCM into the training process (cf. Figure 3). The policy is trained to *control* the AD vehicle to overtake a slower exo-vehicle on a multi-lane road.

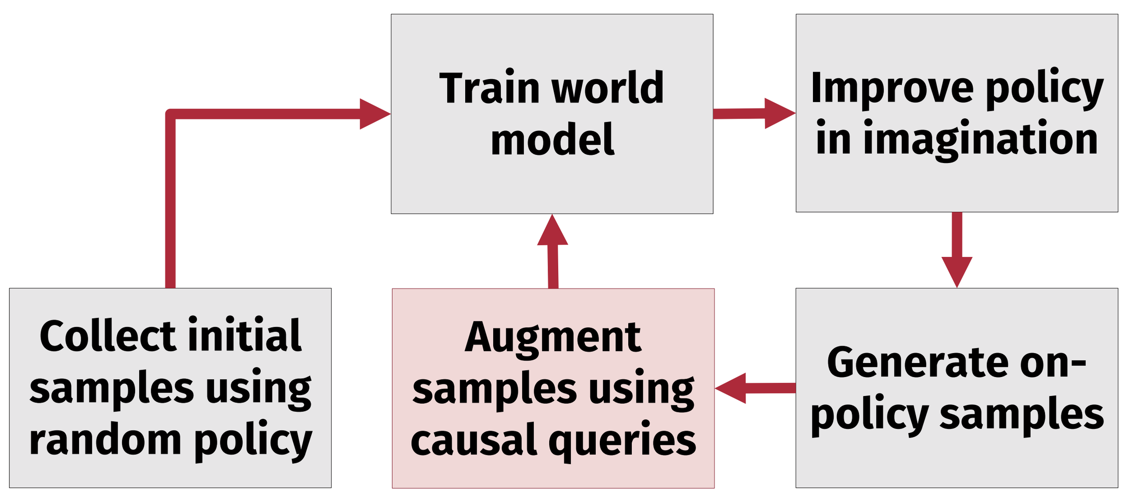

Figure 3: Knowledge integration using causal queries into a model-based RL agent training workflow. (© e:fs TechHub GmbH)

Evaluation of the Knowledge Integration

For the evaluation of the knowledge integration, we use the training scenarios and scenario variations with altered exo-vehicle behavior. We report the overtaking maneuver success rates without collisions for the baseline agent (trained on base scenarios), and knowledge integrated agent (trained on base scenarios, using causal queries for data augmentation). Knowledge integration with causal reasoning significantly improves performance on the scenario variations compared to the baseline agent.

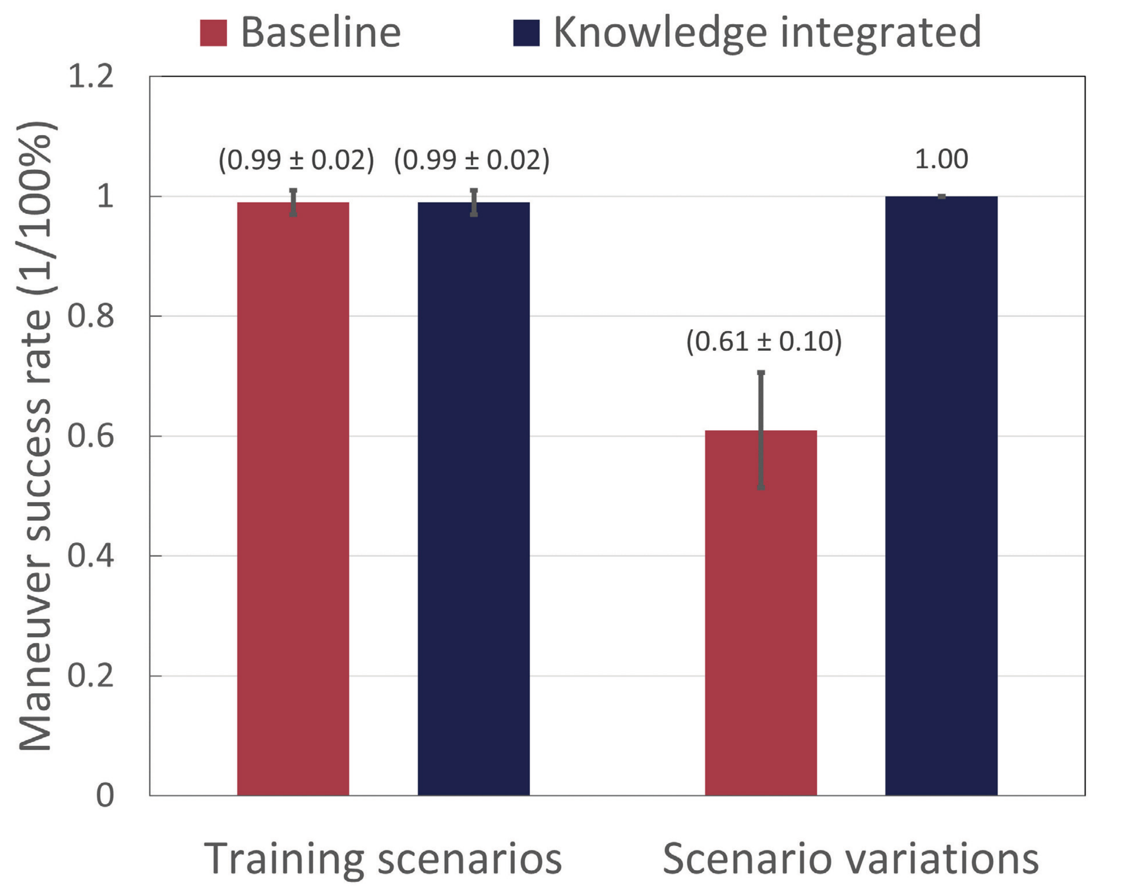

Figure 4: Evaluation of knowledge integrated model-based RL agent against baseline agent. Each evaluation is over 100 scenario episodes. (© e:fs TechHub GmbH)

Reference:

[1] Agarwal, Brunner, Latka, Rudolph: A Causal Model for Physics-Conform Vehicle Trajectories. In IEEE ITSC, 2023.

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KI Wissen is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

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Funded by the European Union NextGenerationEU

Supported by: Federal Ministry for Economic Affairs and Climate Action on the basis of a decision by the German Bundestag

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