KI Wissen Final Event | 21-22 March 2024

A Causal Model of Vehicle Trajectories for Integration of a Priori Knowledge

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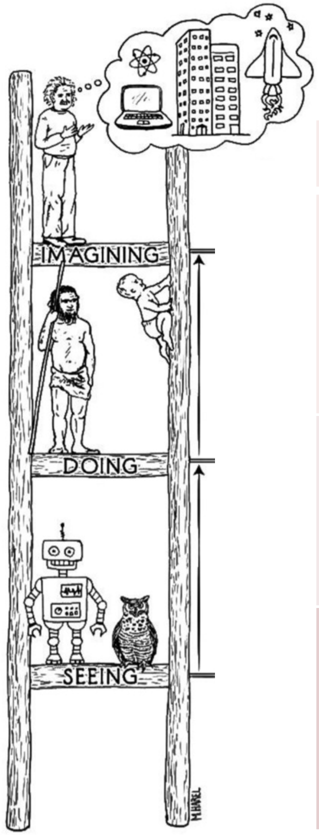
Introduction:
The Causal Revolution

The Causal Revolution

What if we had a formal and systematic way of deriving answers to causal questions in the driving domain?

> Causal modeling provides a formalism to answer questions on all levels of the ladder of causation



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

Structural causal models

Statistical models

Pearl, Mackenzie. *The book of why: the new science of cause and effect*. Basic books, 2018.

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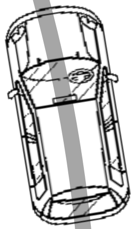
A Causal Model for Vehicle Trajectories

Causal Knowledge about Vehicle Trajectories

Prior knowledge about vehicle trajectories:

- High-level variables (vehicle positions, vehicle velocities, driver actions, etc.)
- Temporal causal relationships of the high-level variables
- Physical constraints on vehicle movement:
  - Constraints on movement between time-steps
  - Coupling between longitudinal and lateral movement



A Structural Causal Model (SCM) for Vehicle Trajectories

Variables (nodes) in our Vehicle-SCM:

- s_t: Vehicle states (positions and velocities)
- o_t: Possibly noisy or missing observations of states
- a_t: Accelerations due to the driver's actions

Generative model: $p(s_{1:T}, a_{1:T}, o_{1:T})$

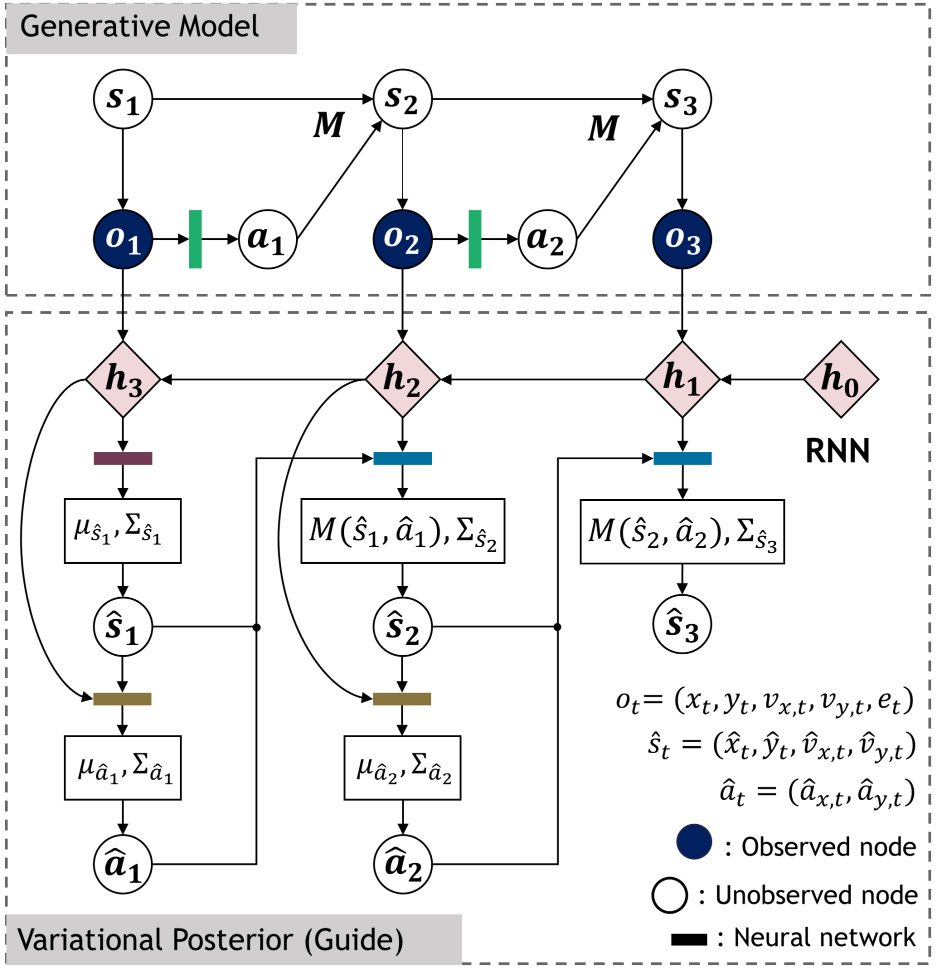
- $o_t \sim p(o_t \mid s_t)$
- $a_t \sim p(a_t \mid o_t)$
- $s_t \sim p(s_{t+1} \mid s_t, a_t) = M(s_t, a_t) + \epsilon_{s_t}$

Simplified vehicle dynamics model

Guide (variational posterior): $q(\hat{a}_{1:T}, \hat{s}_{1:T} | o_{1:T}) \approx p(s_{1:T}, a_{1:T} | o_{1:T})$

- $\hat{a}_t \sim q(\hat{a}_t \mid \hat{s}_t, o_{t:T})$
- $\hat{s}_{t+1} \sim q(\hat{s}_{t+1} \mid \hat{s}_t, \hat{a}_t, o_{t:T})$

Dependence through RNN

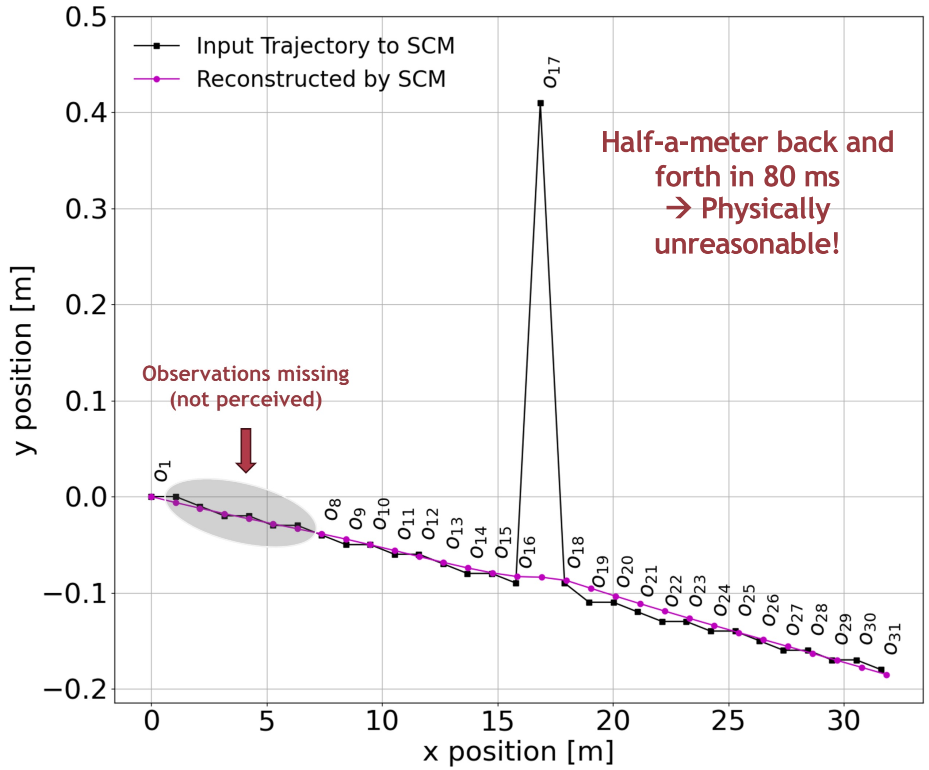


Adapted from Agarwal, Brunner, et al. "A Causal Model for Physics-Conform Vehicle Trajectories." *2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC)*. IEEE, 2023.

Deriving Answers to Associational Causal Queries

Associational query:
"What is the most likely sequence of actions and states given we observed a particular trajectory?"

- Answered using the Guide $q(\hat{a}_{1:T}, \hat{s}_{1:T} | o_{1:T})$ by conditioning on the observation sequence
- Applied to check the physical conformity of observation sequences in AP3.1



Deriving Answers to Counterfactual Causal Queries

Counterfactual query:

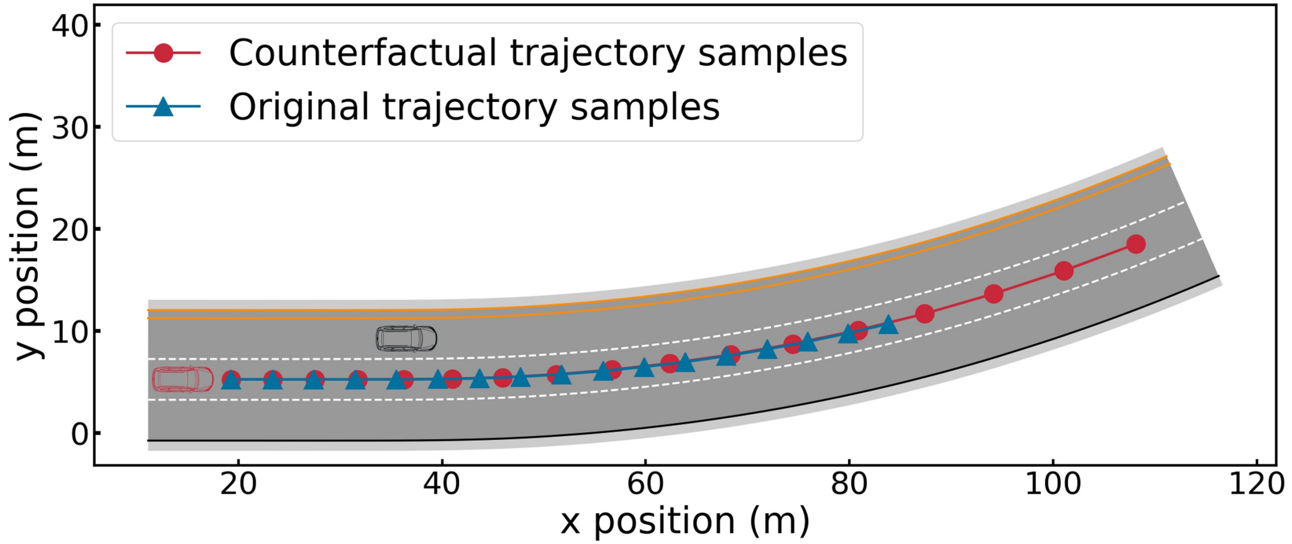
"What would have happened if the vehicle's longitudinal acceleration had been 1 m/s² higher than it was?"

1. **Abduction:** use associational-level query for deriving state and action sequences that explain the observed trajectory using guide

$$q(\hat{a}_{1:T}, \hat{s}_{1:T} | o_{1:T})$$

2. **Intervention in counterfactual model:** modify the action sequence and apply interventional query with modified actions using the generative model

$$p(s_{1:T}, a_{1:T}, o_{1:T} | do(\tilde{a}_{1:T}))$$



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Integration of a Priori Knowledge into Machine Learning Algorithms

Integration of a Priori Knowledge into Machine Learning

- **Question:**

> Can we integrate causal knowledge into Machine Learning using causal queries?

- **Benefits:**
  - Improve robustness on scenarios that are plausible but scarce in the training data distribution
  - Improve data efficiency by making use of causal reasoning instead of vast data collection
  - Steps towards causal explainability of AI decisions

Training of the Baseline Reinforcement Learning Agent

- Training of a model-based reinforcement learner: Dreamer v2 [1, 2]

- Trained the agent to overtake a slower exo-vehicle on a multi-lane road using 1M environment interactions in Carla

- Agent is only trained on a limited set of training scenarios

[1] Hafner, Danijar, et al. "Dream to control: Learning behaviors by latent imagination." *arXiv preprint arXiv:1912.01603* (2019).

[2] Hafner, Danijar, et al. "Mastering atari with discrete world models." *arXiv preprint arXiv:2010.02193* (2020).

Robustness of the Baseline Reinforcement Learning Agent

Checking the robustness of the baseline agent on scenarios with altered exo-vehicle behavior

<u>Scenario variations:</u>

- Exo-vehicle initializes sudden, immediate emergency braking
- **Exo-vehicle increases velocity while ego-vehicle is overtaking**
- Exo-vehicle overlooks ego-vehicle and cuts into the lane

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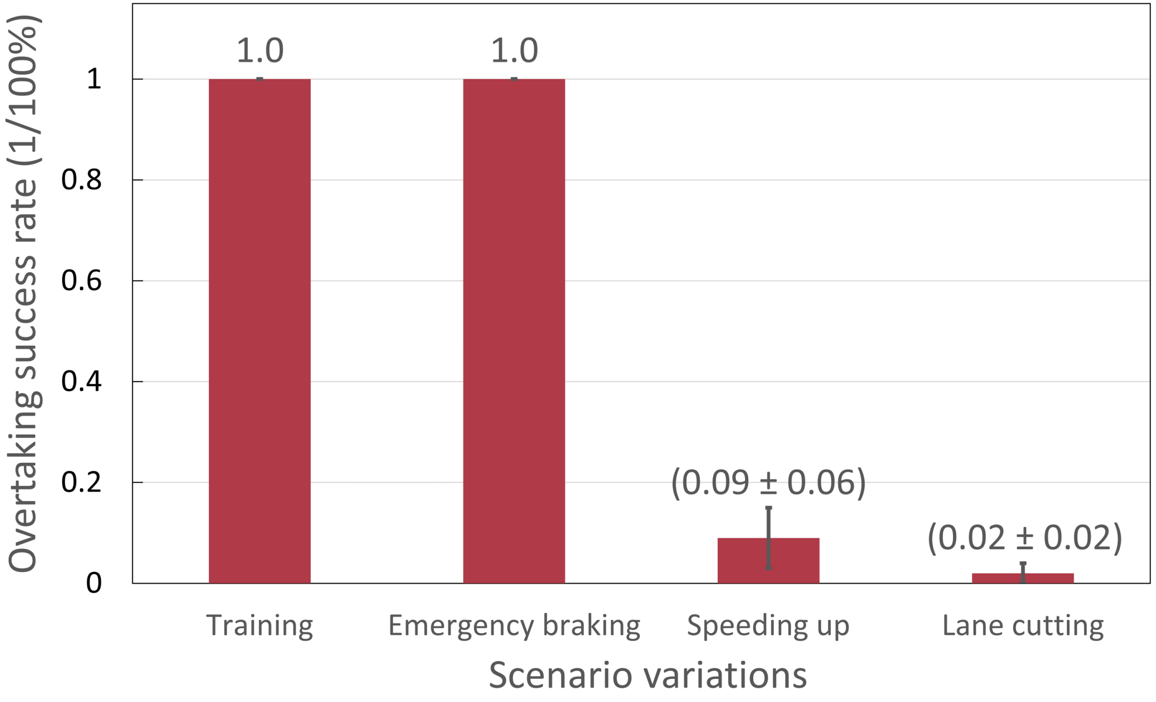
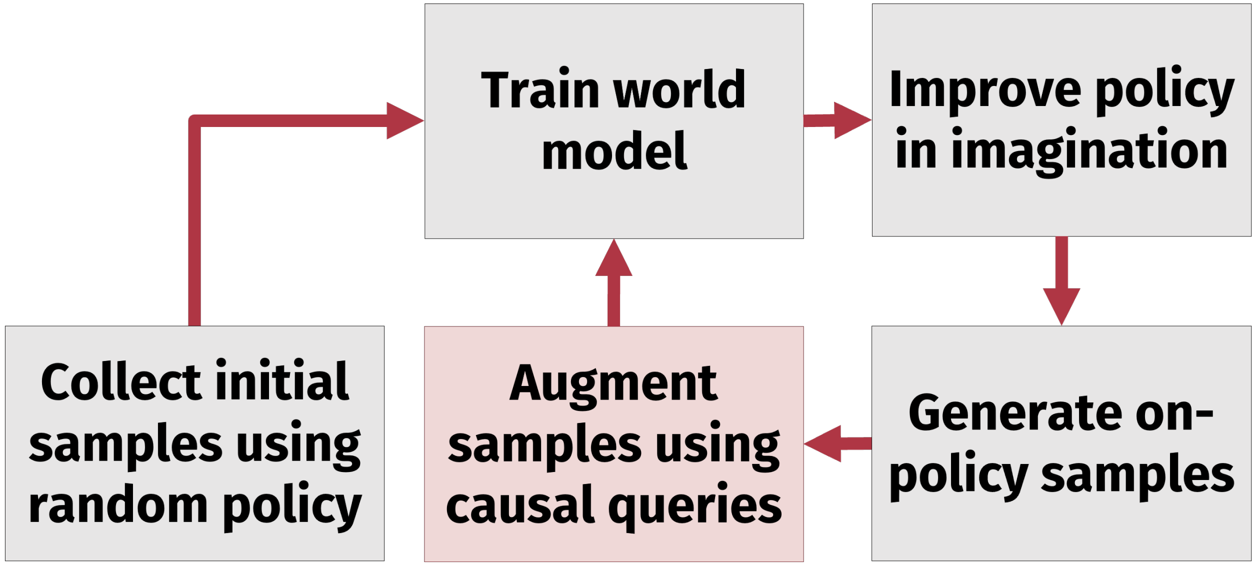


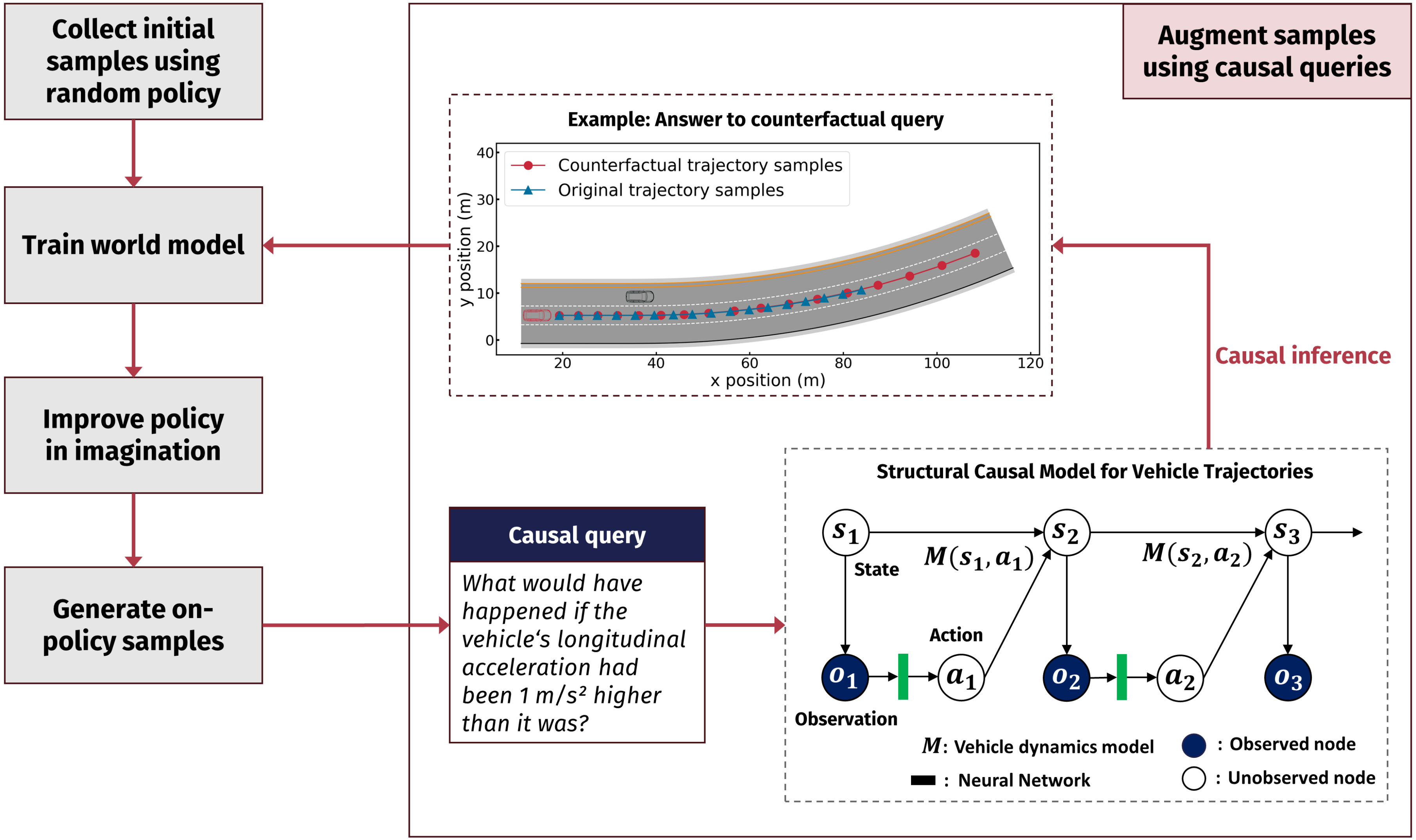
Integration of Knowledge into Reinforcement Learning

Outline of a model-based reinforcement learning algorithm with knowledge integration:

1. Generate samples (run the policy)
2. Train/fit a model (estimate the return)
3. Augment samples using causal queries
4. Improve the policy



Integration of Knowledge into Reinforcement Learning



Robustness of the RL Agent with Knowledge Integration

Evaluation of the overtaking maneuver success rate without collision over 1000 episodes:

- **Baseline:** agent trained on training scenarios
- **Knowledge integrated:** using causal queries

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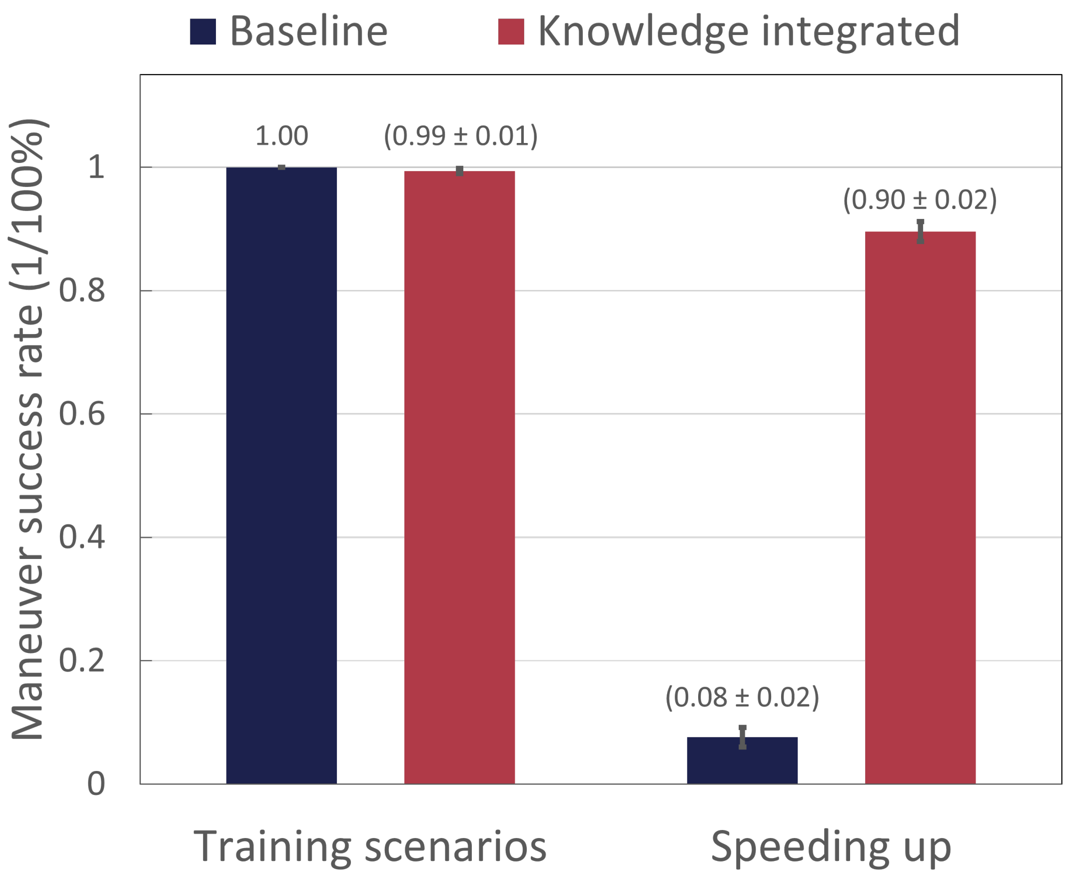

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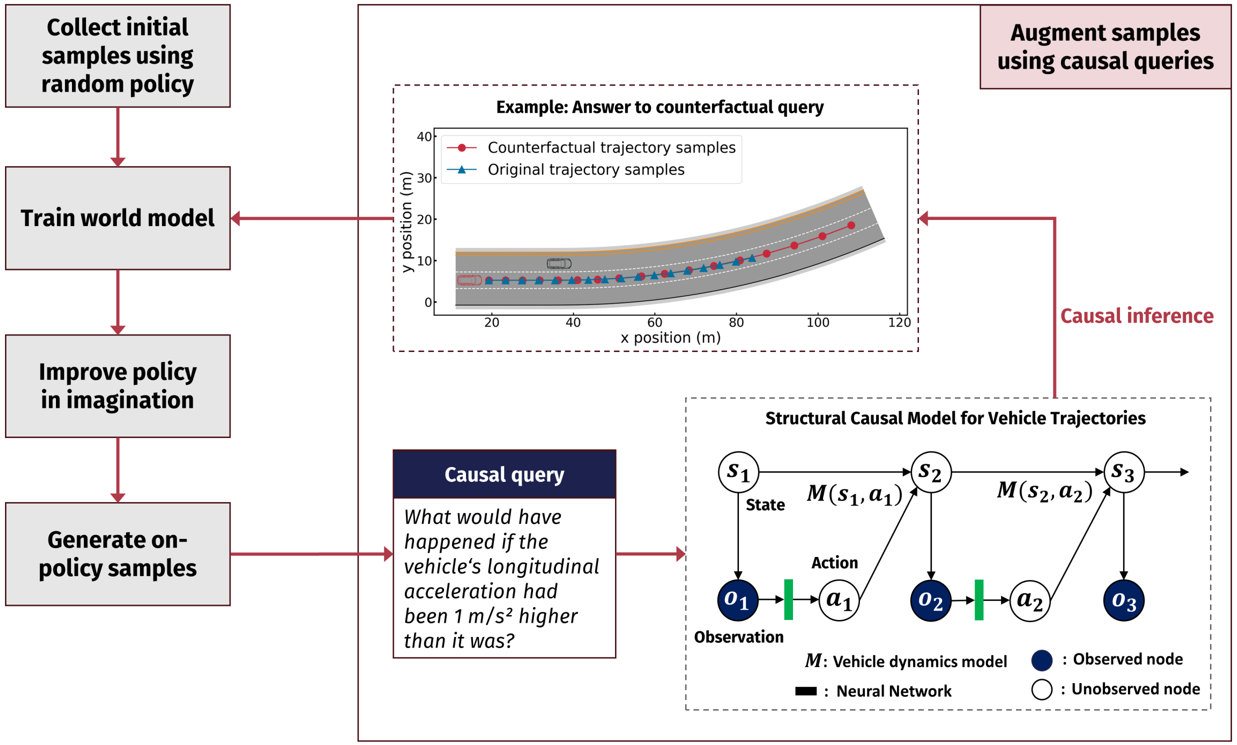
Conclusion

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

- Goal:
  Improve robustness and data efficiency of ML-based functions using causal reasoning
- Concept:
  Application of causal queries to augment training data
- Result:
  Data augmentation using causal queries can significantly improve robustness of ML decisions in plausible scenarios outside the training distribution



KI WISSEN

Automotive AI Powered by Knowledge

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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.

KI FAMILIE

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