Criticality Analysis – Method

8.3 | Modeling and analysis of causal relations

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PROJECT of the PEGASUS FAMILY

VERIFICATION VALIDATION METHODS

The challenge: Causal relations from data

- Analysis of criticality phenomena requires understanding of cause-effect relationship
- Correlation does not imply causation
- Confounding effects lead to wrong understanding of causal relations

The solution: Causal inference

Causal graphs to model criticality phenomena allow us to systematically identify and understand causal relations leading to criticality.

- Causal graphs to encode causal relations from expert knowledge
- Intervention metrics to quantify causal impact
- Iterative loop to plausibilize causal graph with experts and observational data

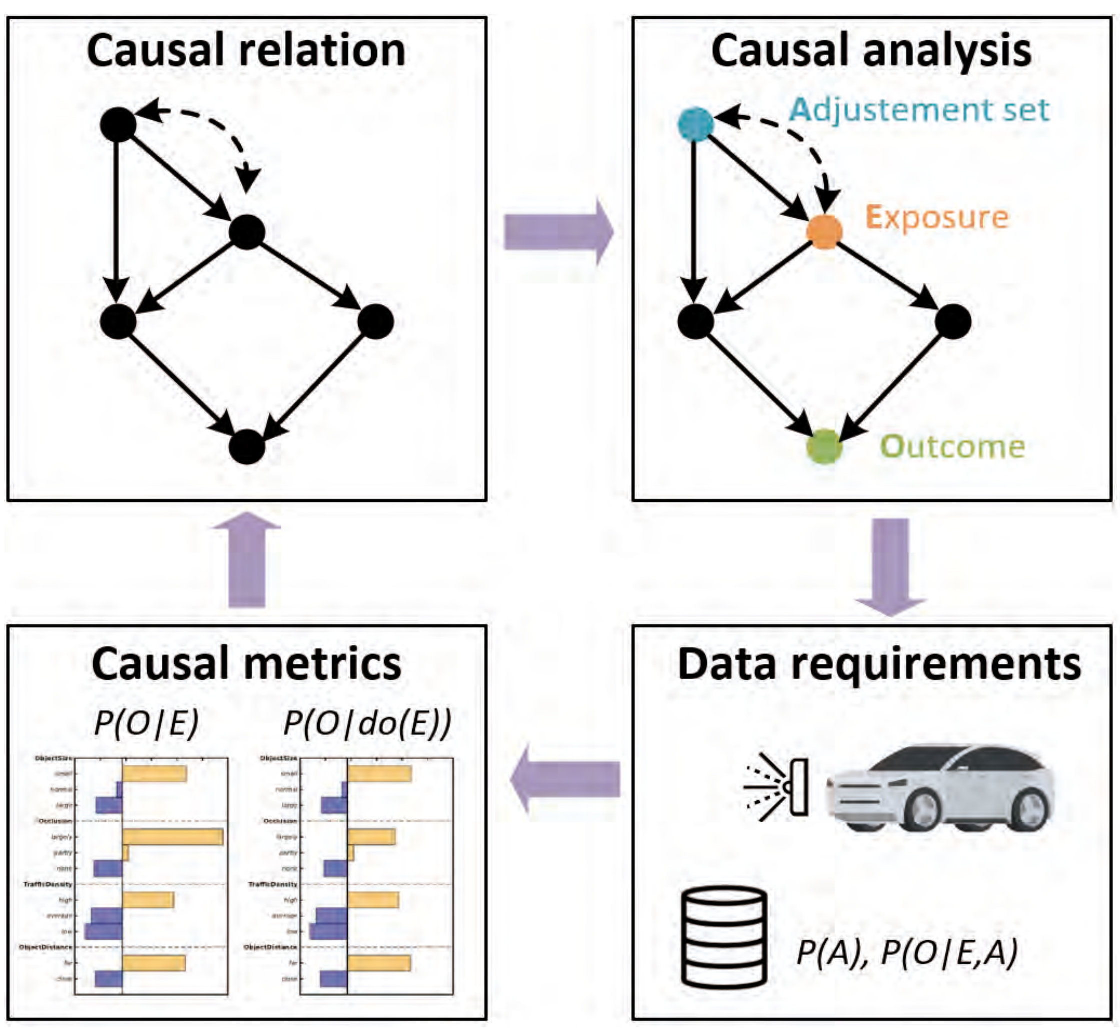


Figure 1: Method workflow for modelling and analysis of causal relations (©Robert Bosch GmbH).

Inputs

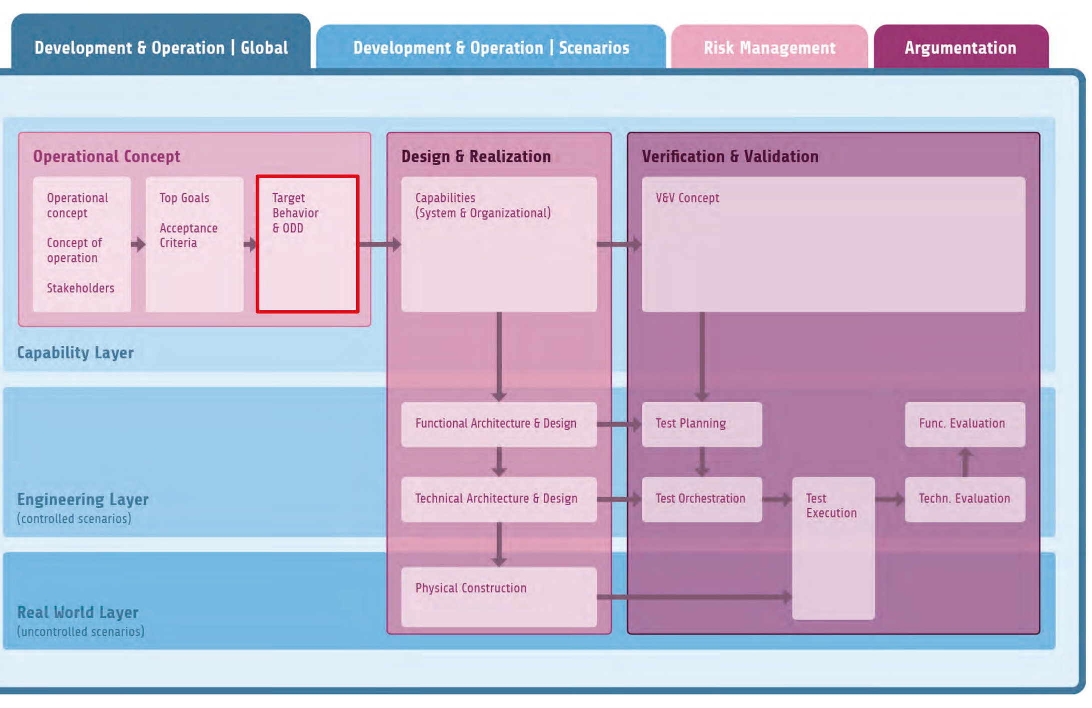
- Criticality phenomena for analysis
- Expert knowledge on causal relations
- Observational data on phenomena

Outputs

- Data acquisition requirements
- Plausibilized causal relations
- Quantified causal impact of criticality phenomena

Applications of causal inference

For complex automated driving systems a deterministic model is often not feasible. Causal inference enables reasoning of cause-effect relationships on the basis of probabilistic causation from data. It can be used on all abstraction levels ranging from criticality analysis of traffic situations to detailed analysis of perception subsystems.



Confounding and Adjustment sets

Correlation $P(Per|Lum)$ influenced by confounding Weather node. Intervention $P(Per|do(Lum))$ ajdusts for confounding providing a causal metric.

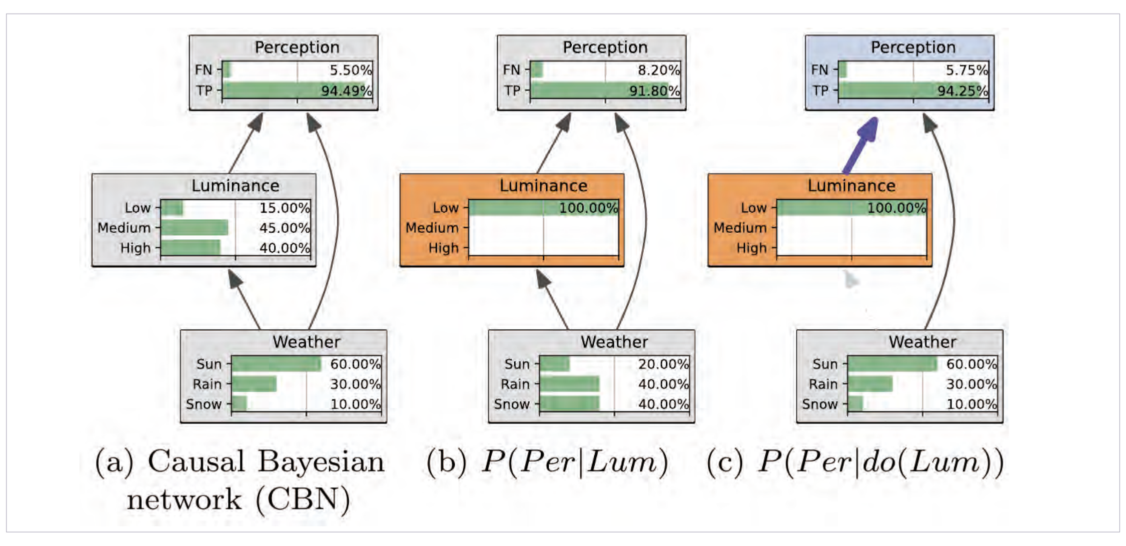
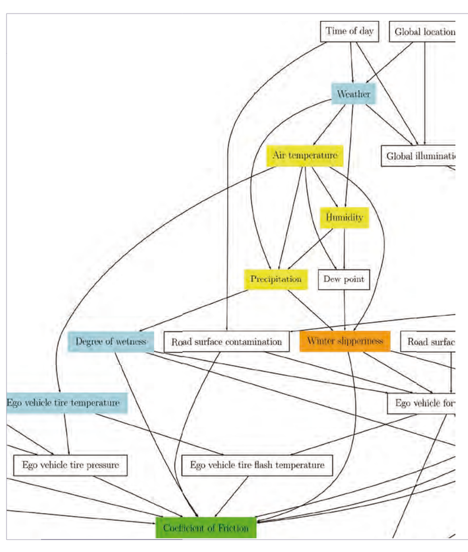


Figure 2: Confounding effect and difference between conditional probability and intervention (©Robert Bosch GmbH)

Backdoor-/Frontdoor adjustment is used to calculate causal intervention metric from observational data.



$$P(O|do(E)) = \sum_{A} P(A)P(O|A,E)$$

$E = \{Winter\ slipperiness\}$
$O = \{Coefficient\ of\ Friction\}$
$A_1 = \{Air\ temperature, Humidity, Precipitation\}$
$A_2 = \{Weather, Degree\ of\ wetness,$ $Ego\ vehicle\ tire\ temperature\}$

Figure 3: Minimal adjustment set identification and backdoor adjustment formula of causal graph for friction coefficient (©DLR e.V.).

Model quality and plausibilisation

Indicator functions used as necessary condition for correctly modelled causation. Iterative refinement of causal graph to align expert knowledge with data.

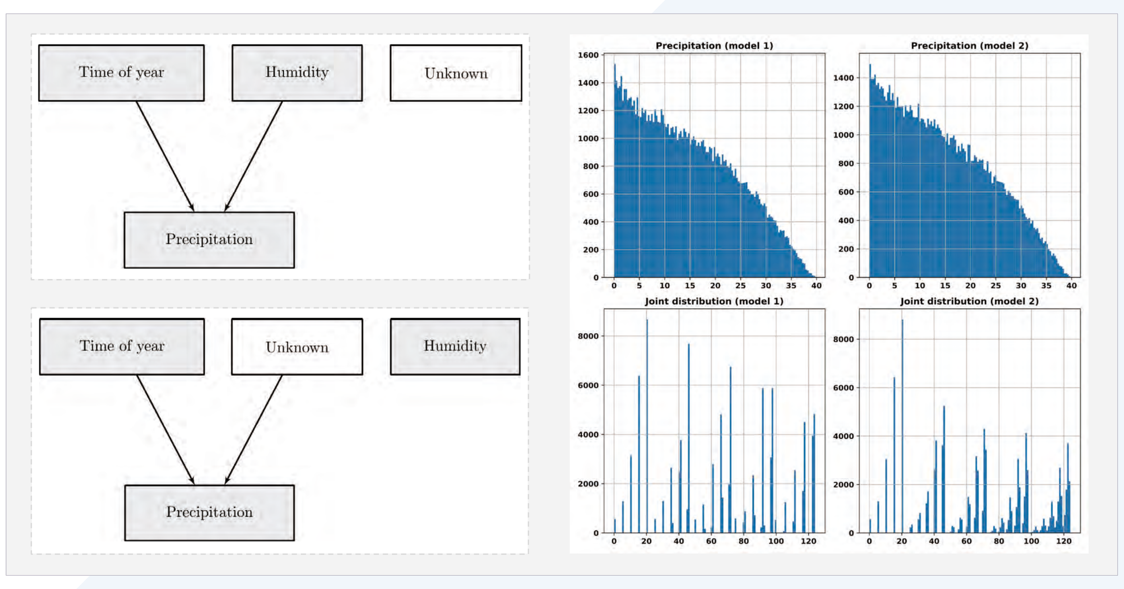


Figure 4: Comparison of assumed cause-effect relations (©DLR e.V.)

Key Artefacts

References:

[1] Koopmann, Tjark, et al. "Grasping causality for the explanation of criticality for automated driving." arXiv preprint arXiv:2210.15375 (2022).

[2] Gansch, Roman, et al. "Causal inference for safety analysis of automated driving." to be submitted

Partners

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VDA LEITINITIATIVE

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