

VERIFICATION VALIDATION METHODS



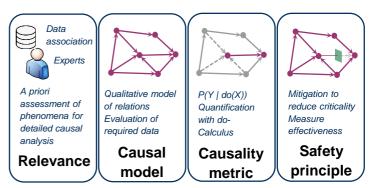
MODELING AND ANALYSIS OF CAUSAL RELATIONS

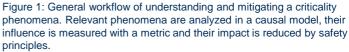
Understanding the causality behind criticality phenomena

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Causal relations for phenomena

- Causal theory applied to problem of understanding criticality phenomena
- Modeling of criticality phenomena with causal models
- Causality instead of correlation
- Measuring causality with metrics
- Mitigating causal influences with safety principles





Causal models and metrics

We demonstrate the application of causality theory with an example from camera perception. As criticality phenomena the illumination and its effect on the performance is analyzed with weather as confounding effect.

To emphasize the importance of the causal analysis we analyze this example with exemplary data in a causal Bayesian network. The analysis shows that a correlational metric such as the conditional probability *P*(*Camera | Illum.*) leads to a wrong interpretation. The causal intervention metric

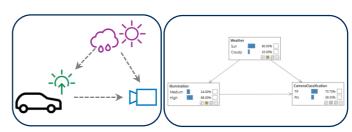


Figure 2: Example of a causal model for camera perception. Analysis is done on the *Illumination* node as exposure on the *CameraClassification* node as outcome. The *Weather* node is a confounding effect and has a strong influence the result of the evaluation.

P(Camera | do(Illum.)) calculated with the do-calculus exposes the direct causal effect from the investigated phenomena. A strong deviation between correlation and causal metric emerges due to the confounding path via the weather node.

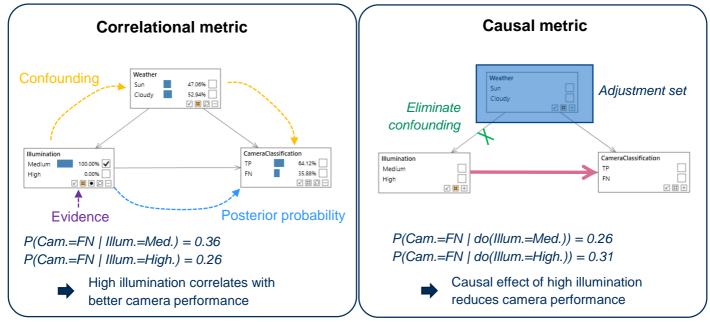


Figure 3: Difference between a correlational and causal analysis on the camera perception example.



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Modeling of Causal Relations

- Causality cannot be inferred from data
 - \rightarrow Requires modeling of assumptions
- Vertices must be random variables
- Low dimensional outcome spaces are preferred
- Edges encode assumptions about causal connections
- CP is represented as binary variable
- Modeling of CR is enhanced inside an iteration cycle

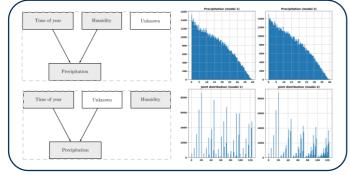


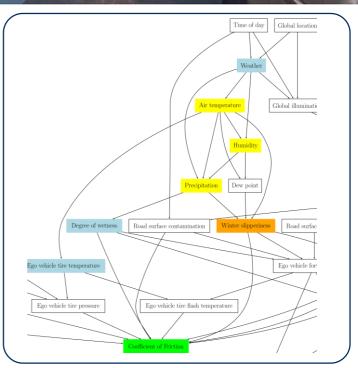
Figure 4: Comparison of the assumed causalities (model 1, upper) with the fabricated reality (model 2, lower). Compared variables are marked in light grey.

Assessment of model quality

We use two causality indicator functions in said iteration cycle. For a criticality metric $\varphi: S \rightarrow [0, 1]$ and a variable *X* with outcome in {*CP*, ¬*CP*}, the explanation of the measured criticality due to the criticality phenomenon is given as

$$\sigma = 1 - \frac{E(\varphi|do(X = \neg CP))}{E(\varphi)}$$

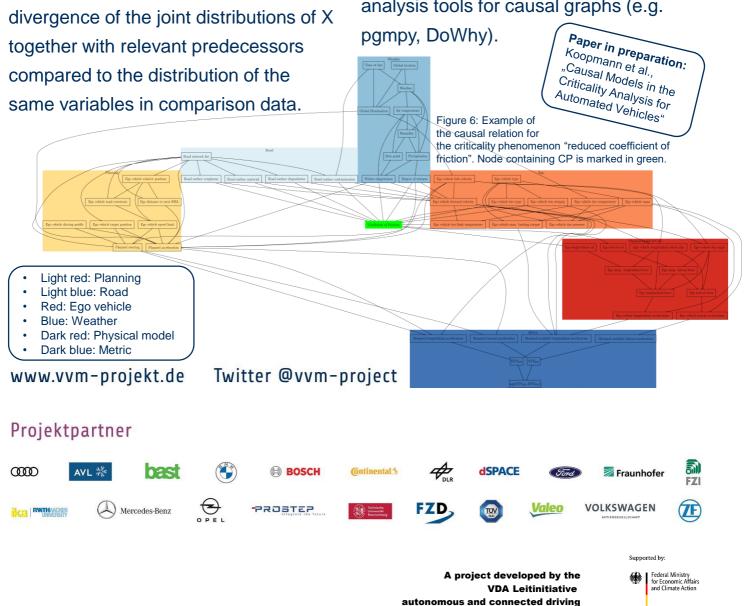
The Explanation of the emergence of CP is defined as the Kullback-Leibler





Example on the left: $\rho = 0.43$, where $\rho = 0$ would indicate equality. Camera classification example: $\sigma = 0.1$. $\sigma = 0$ indicates no explanation, while $\sigma = 1$ indicates perfect explanation. Since ρ is a purely associational quantity it should only be understood as a necessary condition for correct causality.

Tool support for modeling & analysis For analysis we rely on the graph description language DOT. It offers broad compatibility with graph visualization tools (e.g. Graphviz), easy integration into common IDEs (e.g. Eclipse, VS Code) and support in analysis tools for causal graphs (e.g.



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