Causal Bayesian Networks for Data-driven Safety Analysis of Complex Systems

Roman Gansch*, Lina Putze*, Tjark Koopmann, Jan Reich, and Christian Neurohr

IMBSA, 25th September 2025

*These authors contributed equally to this work

How to derive a comprehensive understanding of fault and failure propagation within complex safety-critical systems?

Overview

Hierarchy of Causality

Causal Bayesian Networks

- Modelling
- Form Correlation to Causation

Causal Safety Analysis

- Fault Trees vs. Causal Bayesian Networks
- Importance Metrics

Summary

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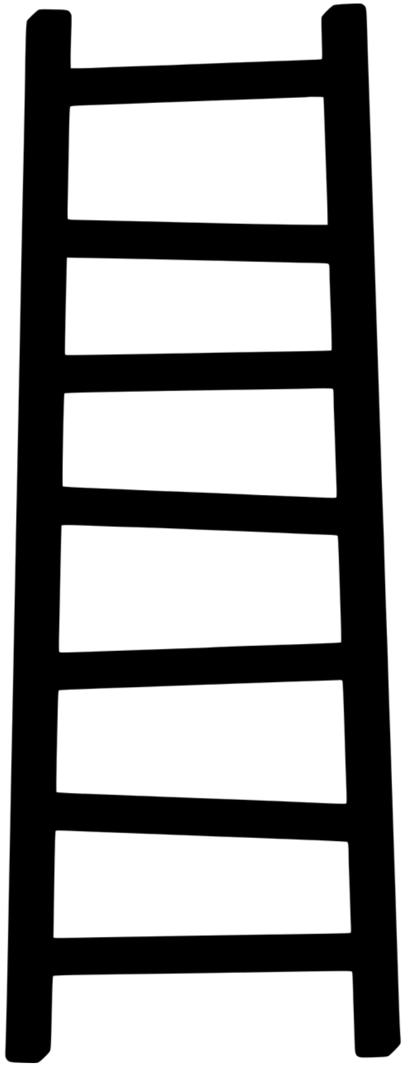
Hierarchy of Causality



Counterfactuals: ‘If X had occurred, what would have been Y?’

Intervention: ‘If I do X, how will it change Y’

Association: ‘If I see X, what does it tell me about Y?’

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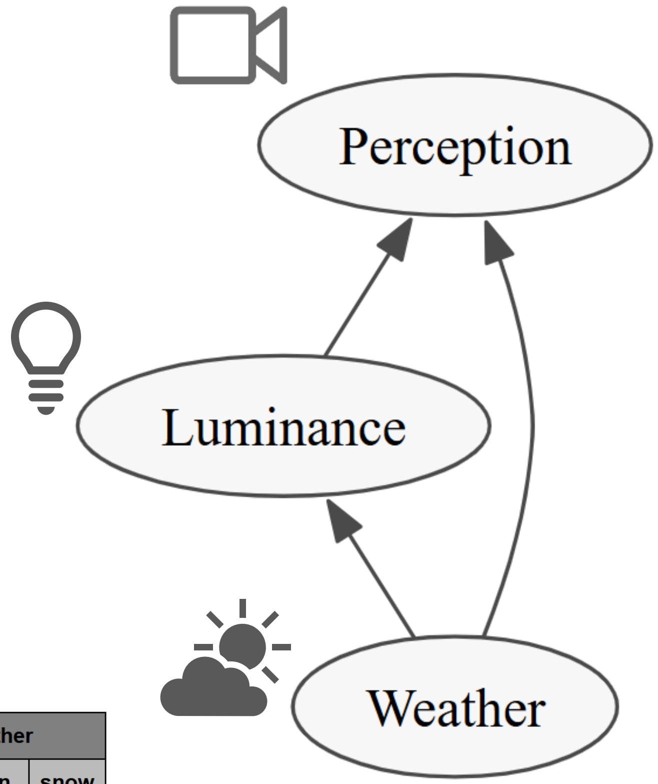
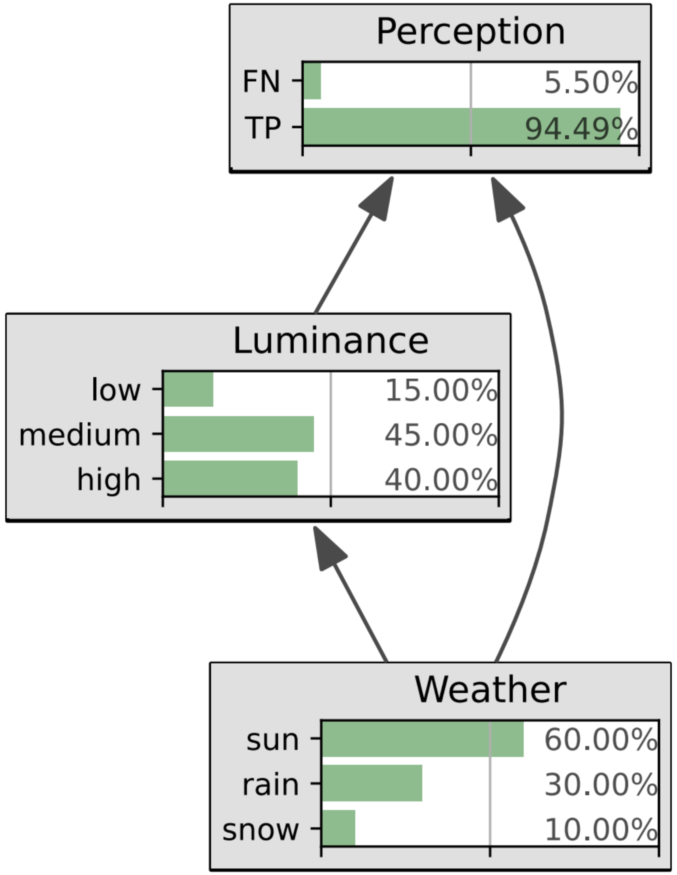
Causal Bayesian Networks
Modelling

		Perception	
Luminance	Weather	FN	TP
low	sun	0.0400	0.9600
	rain	0.0750	0.9250
	snow	0.1100	0.8900
medium	sun	0.0350	0.9650
	rain	0.0700	0.9300
	snow	0.0900	0.9100
high	sun	0.0400	0.9600
	rain	0.0800	0.9200
	snow	0.1050	0.8950

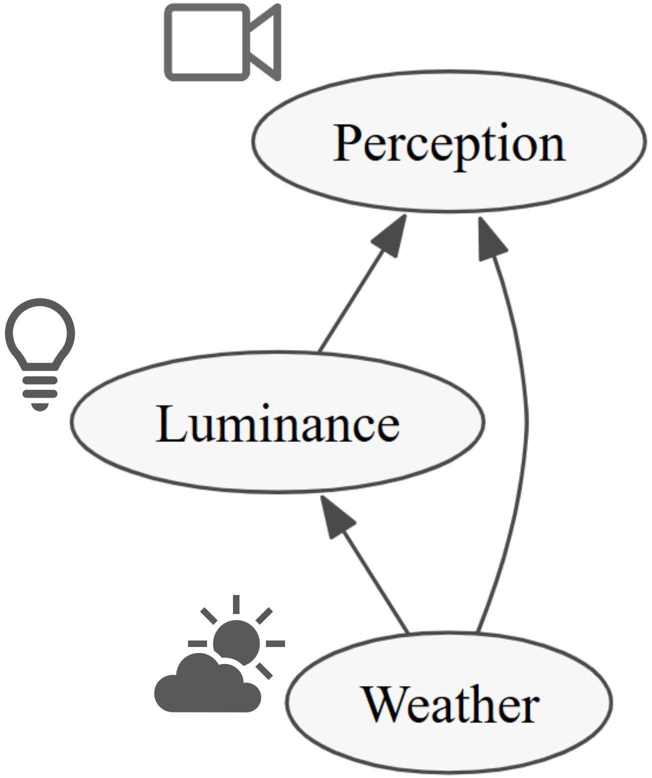
	Luminance		
Weather	low	medium	high
sun	0.0500	0.4000	0.5500
rain	0.2000	0.6000	0.2000
snow	0.6000	0.3000	0.1000

Weather		
sun	rain	snow
0.6000	0.3000	0.1000



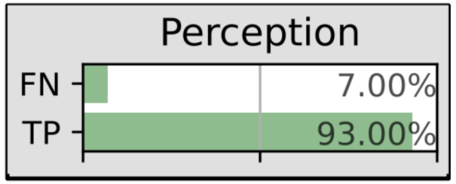


Causal Bayesian Networks
Modelling

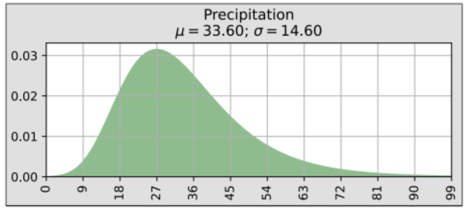


Variables

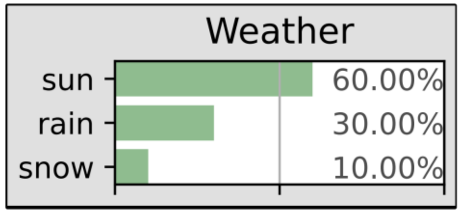
Dichotomous:



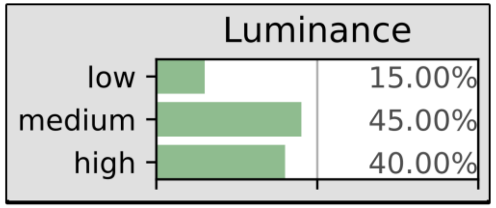
Continuous:



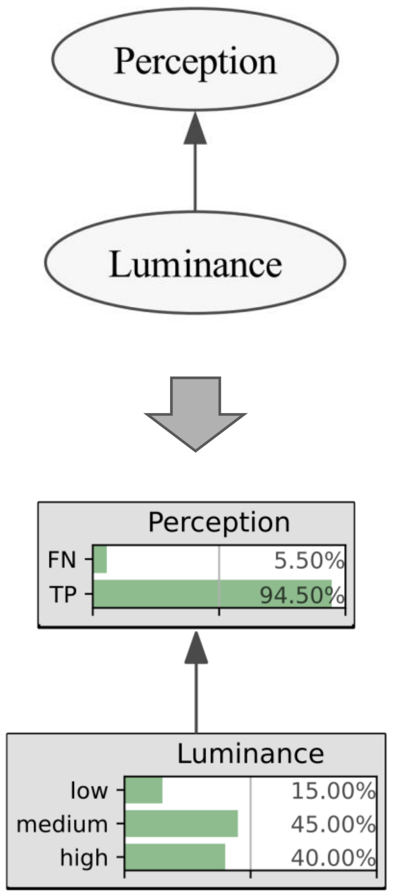
Categorical:



Ranked:

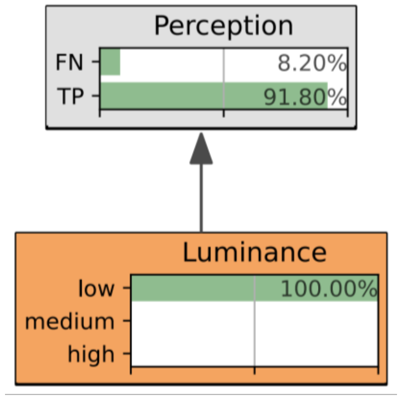


Causal Bayesian Networks
From Correlation to Causation

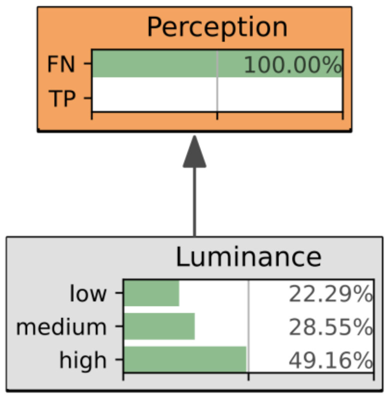


Correlation

$P(Per|Lum = low)$

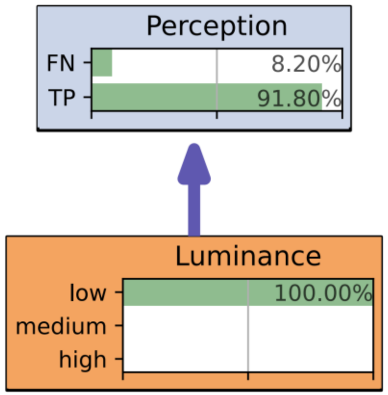


$P(Lum|Per = FN)$

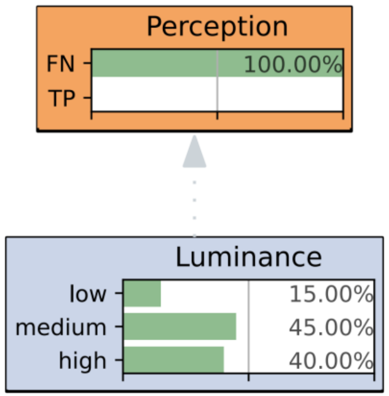


Causation

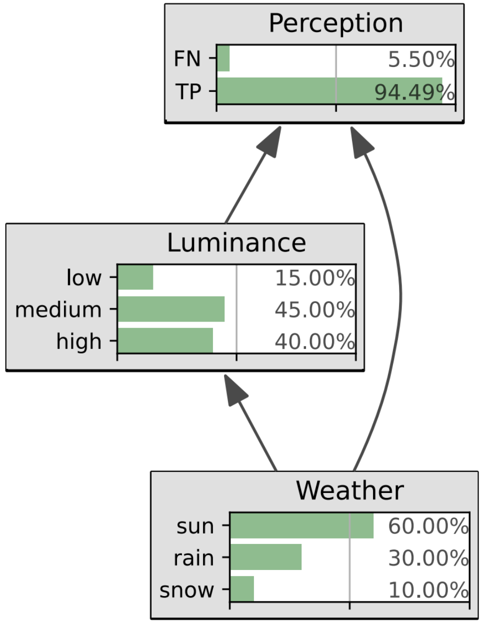
$P(Per|do(Lum = low))$



$P(Lum|do(Per = FN))$



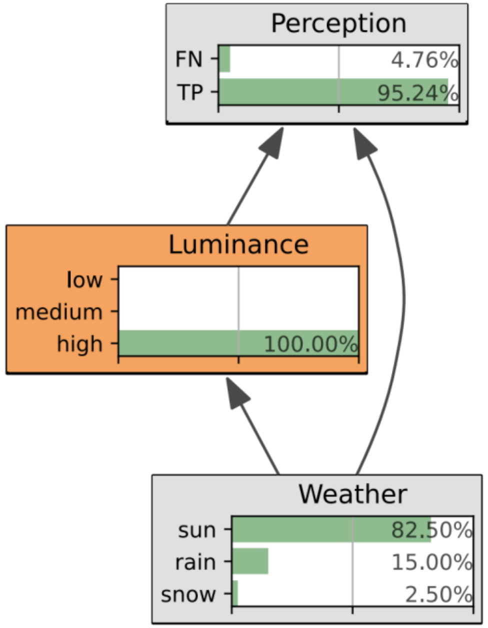
Causal Bayesian Networks
From Correlation to Causation

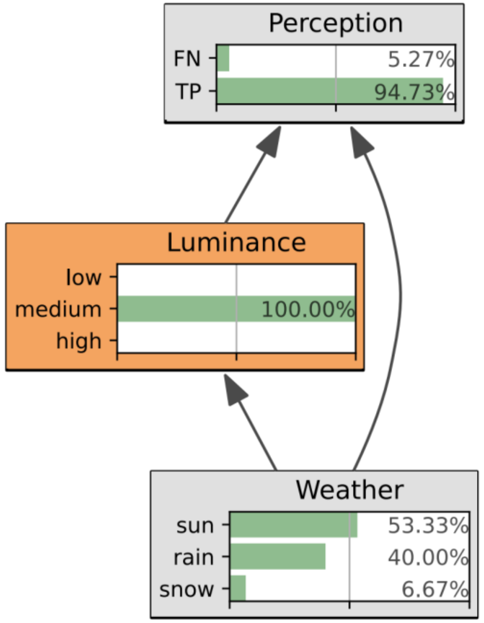


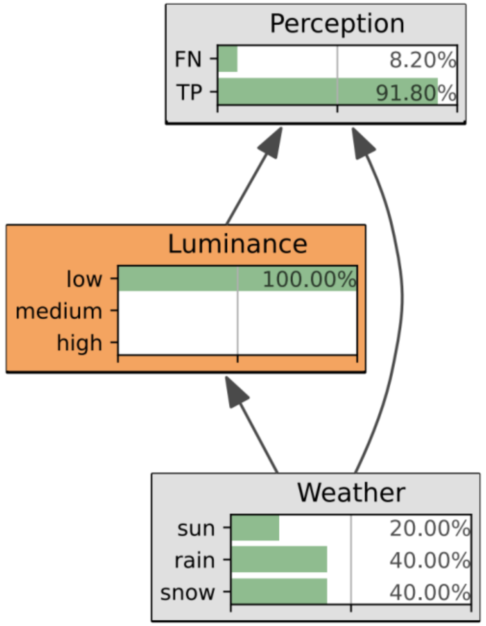
Probability:

$P(Per = FN) = 5.50\%$

Correlation







Conditional Probability:

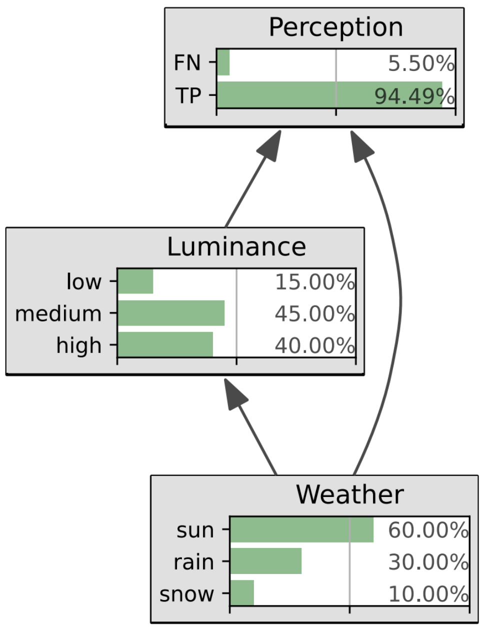
$P(Per = FN | Lum = high) = 4.76\%$

$P(Per = FN | Lum = med.) = 5.27\%$

$P(Per = FN | Lum = low) = 8.20\%$

Causal Bayesian Networks

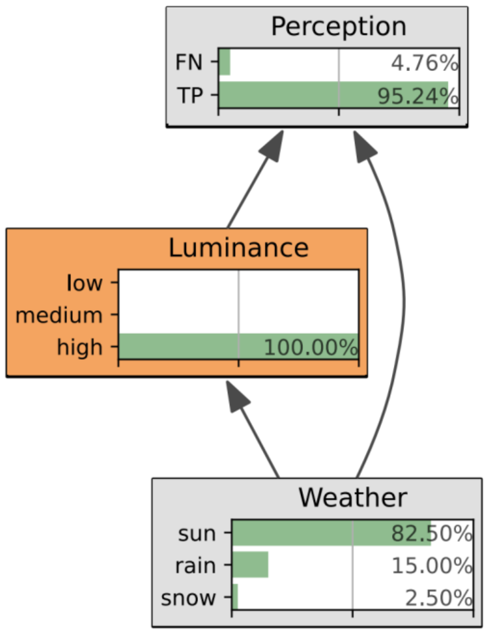
From Correlation to Causation



Probability:

$$P(Per = FN) = 5.50\%$$

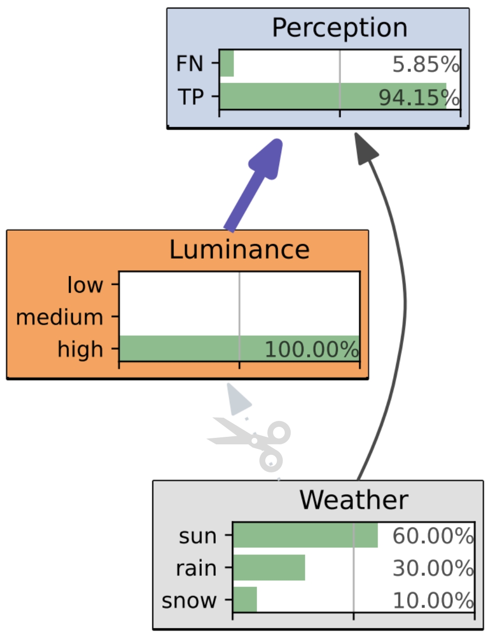
Correlation



Conditional Probability:

$$P(Per = FN|Lum = high) = 4.76\%$$

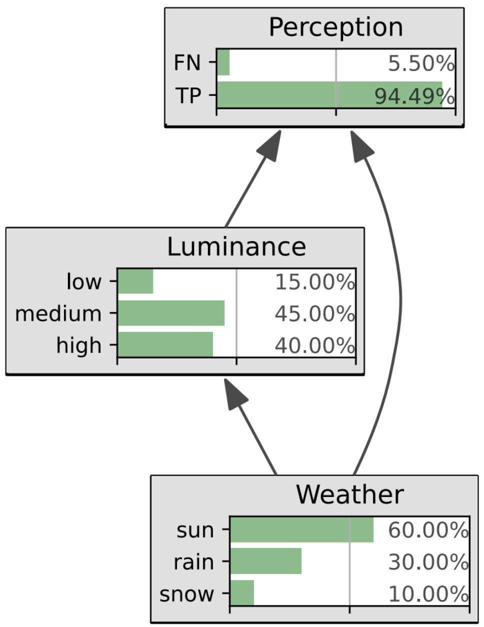
Causation



Interventional Probability:

$$P(Per = FN|do(Lum = high)) = 5.85\%$$

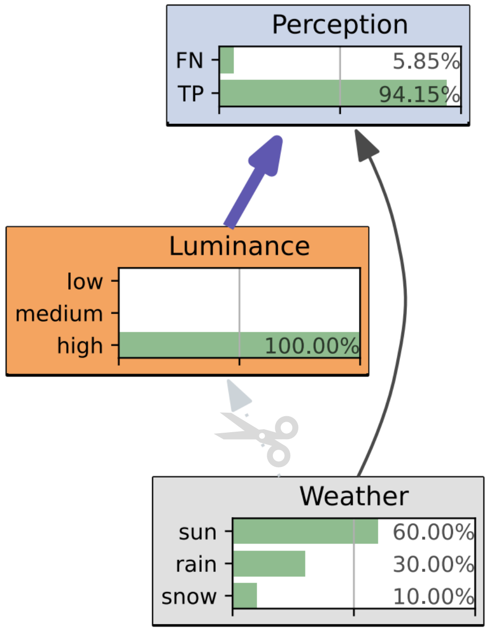
Causal Bayesian Networks
From Correlation to Causation

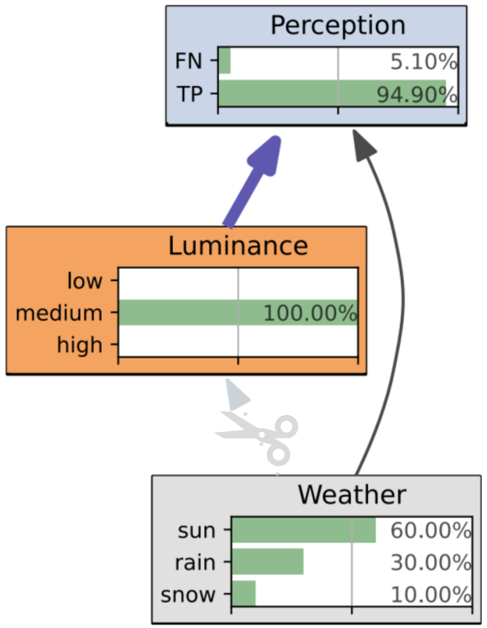


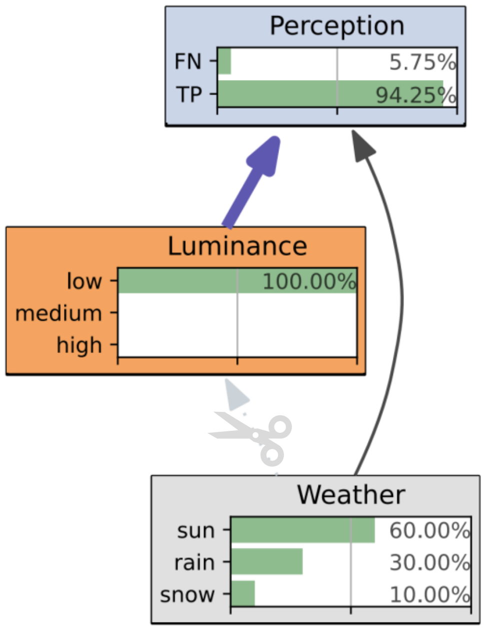
Probability:

$$P(Per = FN) = 5.50\%$$

Causation







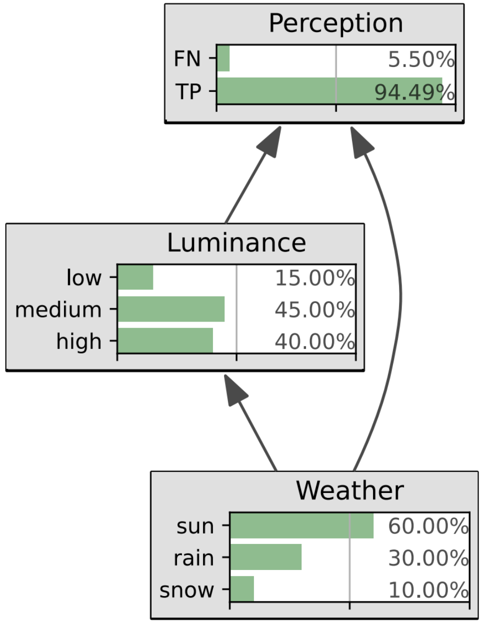
Interventional Probability:

$P(Per = FN|do(Lum = high)) = 5.85\%$

$P(Per = FN|do(Lum = med.)) = 5.10\%$

$P(Per = FN|do(Lum = low)) = 4.76\%$

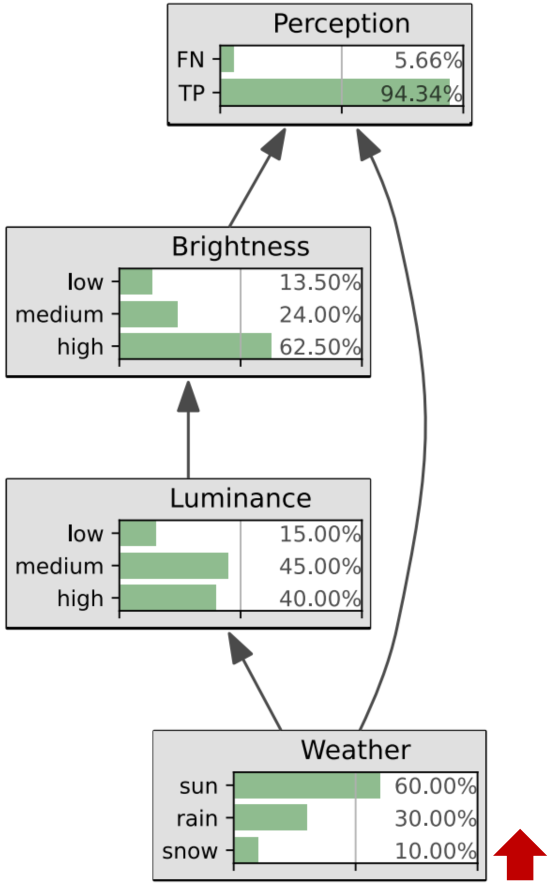
Causal Bayesian Networks
From Correlation to Causation



Probability:

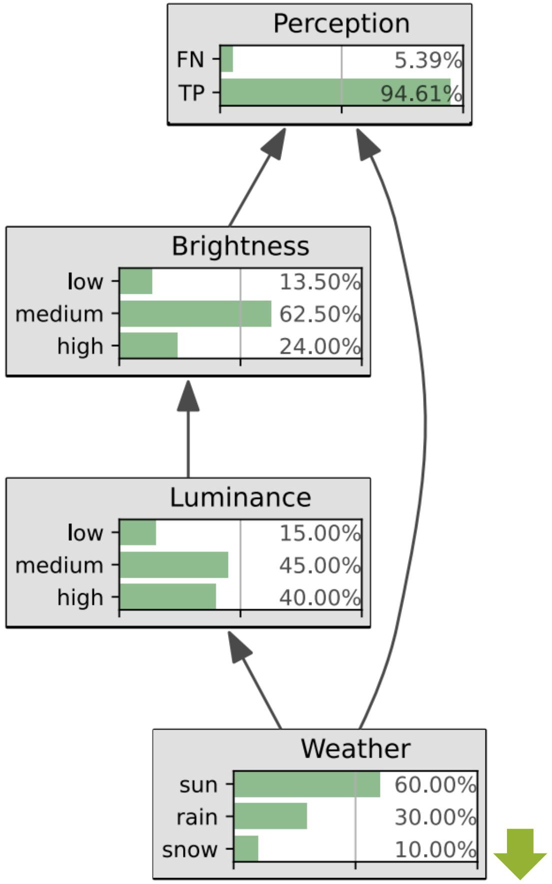
$$P(Per = FN) = 5.50\%$$

Correlation



$$P(Per = FN) = 5.66\%$$

Causation



$$P(Per = FN) = 5.39\%$$

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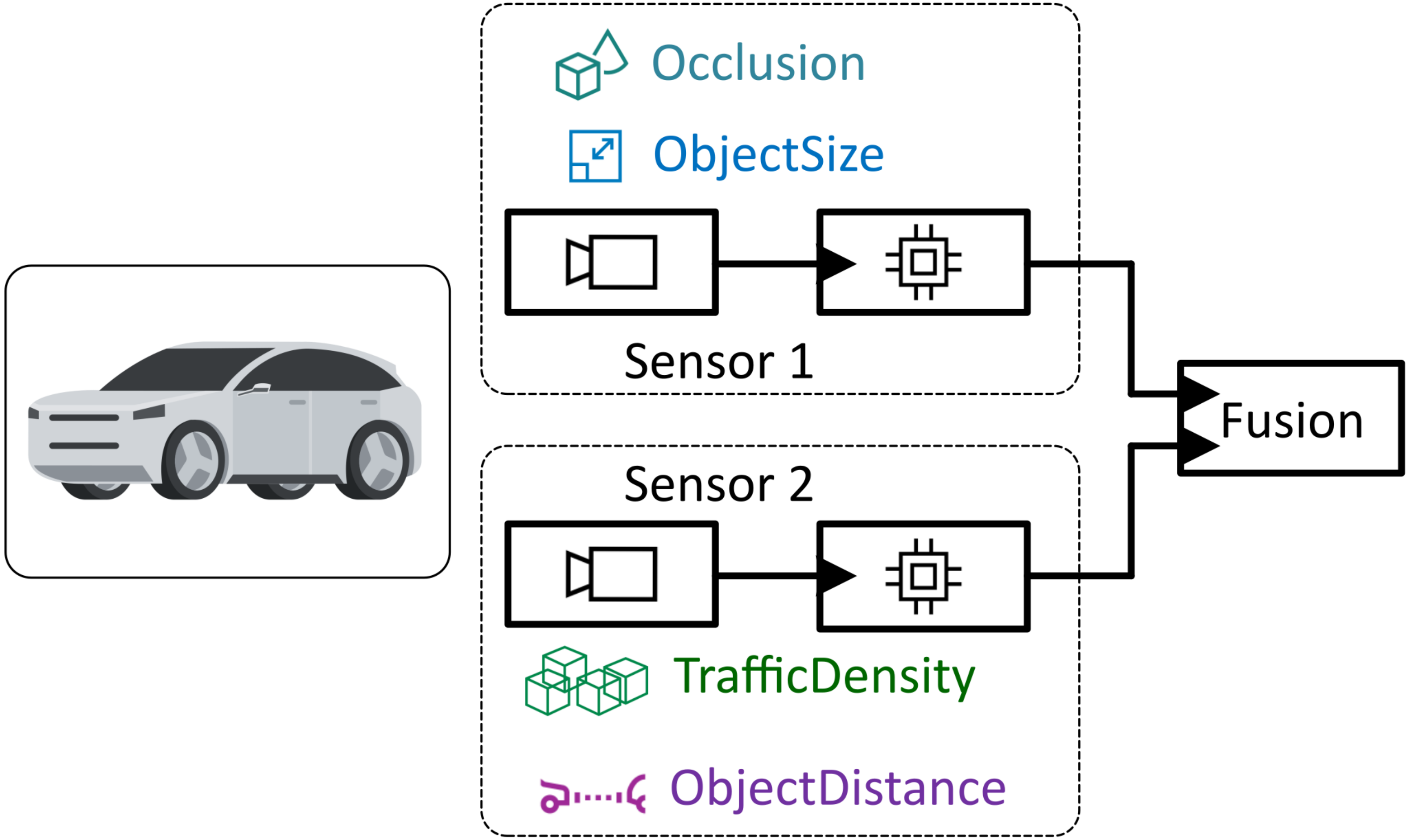
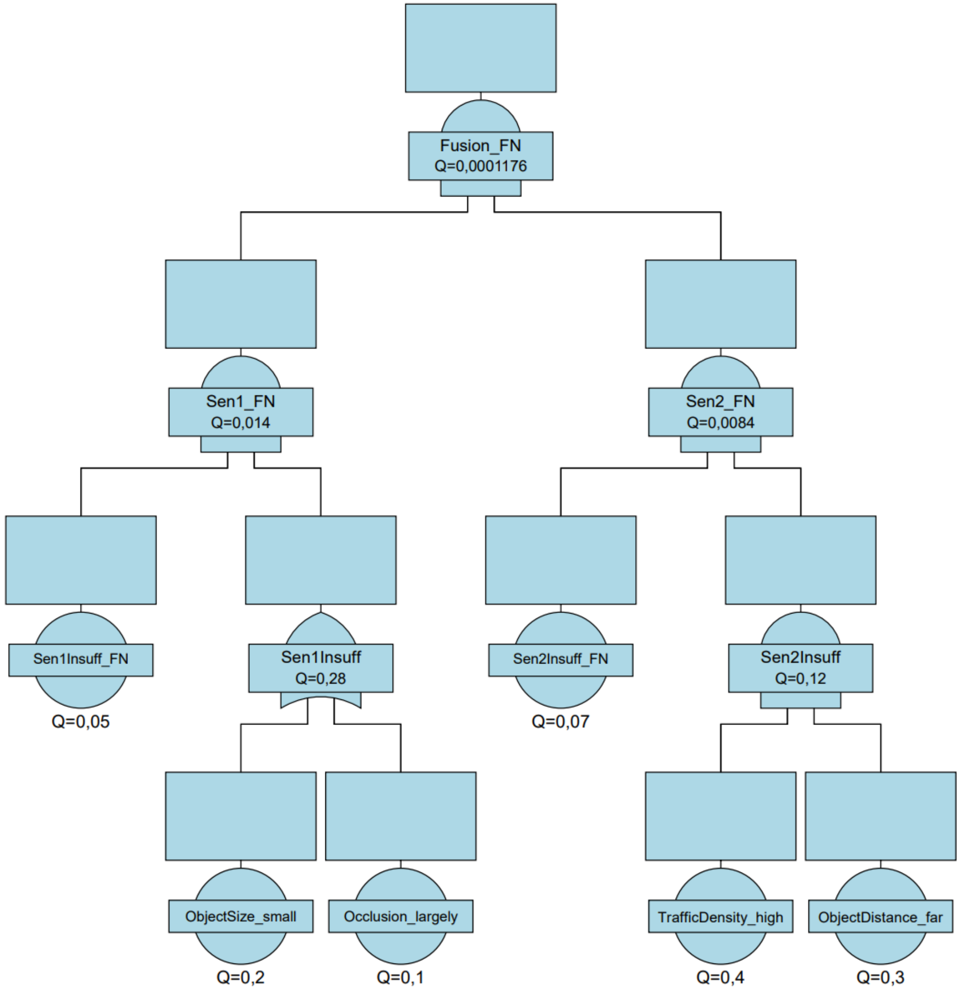
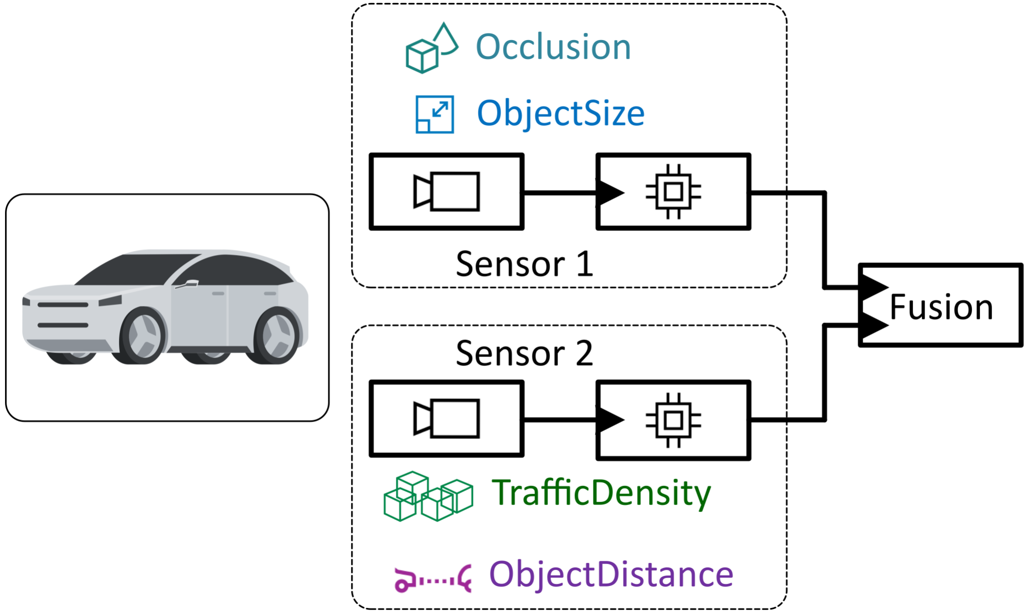
Causal Safety Analysis
Example



Causal Safety Analysis
Fault Trees vs. Causal Bayesian Networks

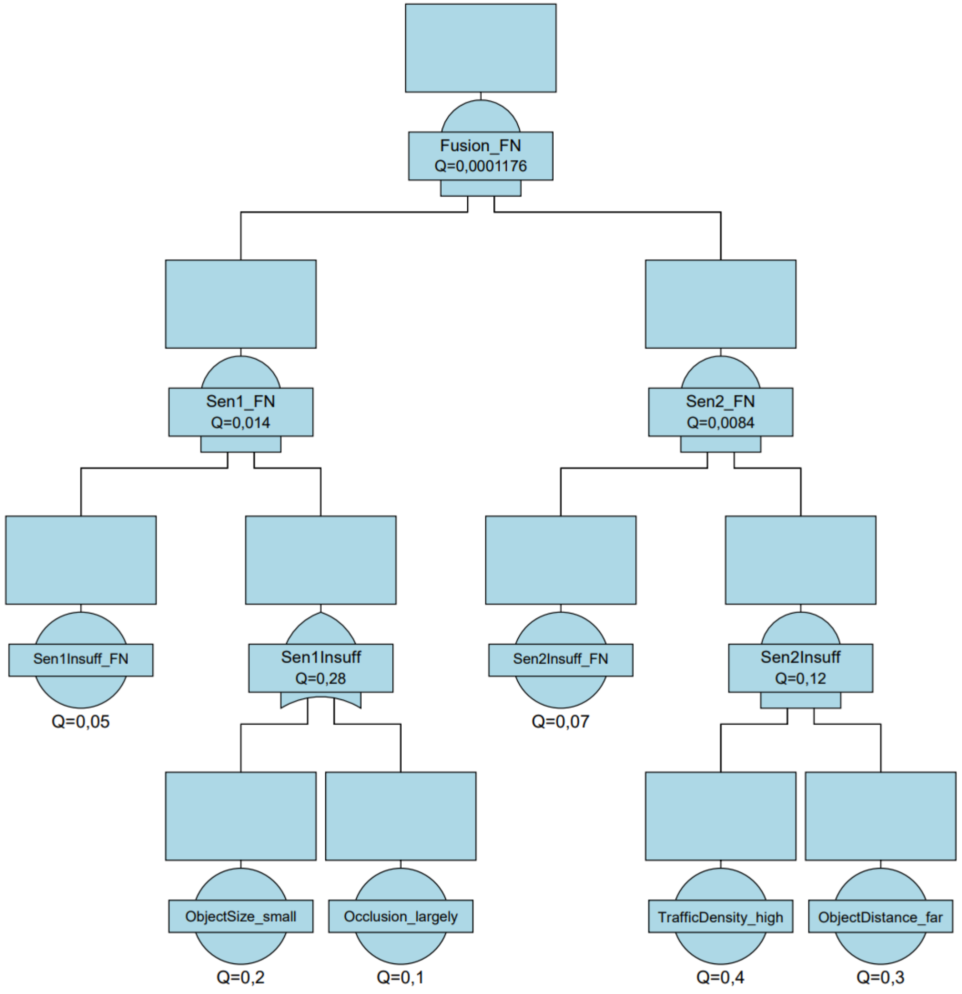
Fault Tree



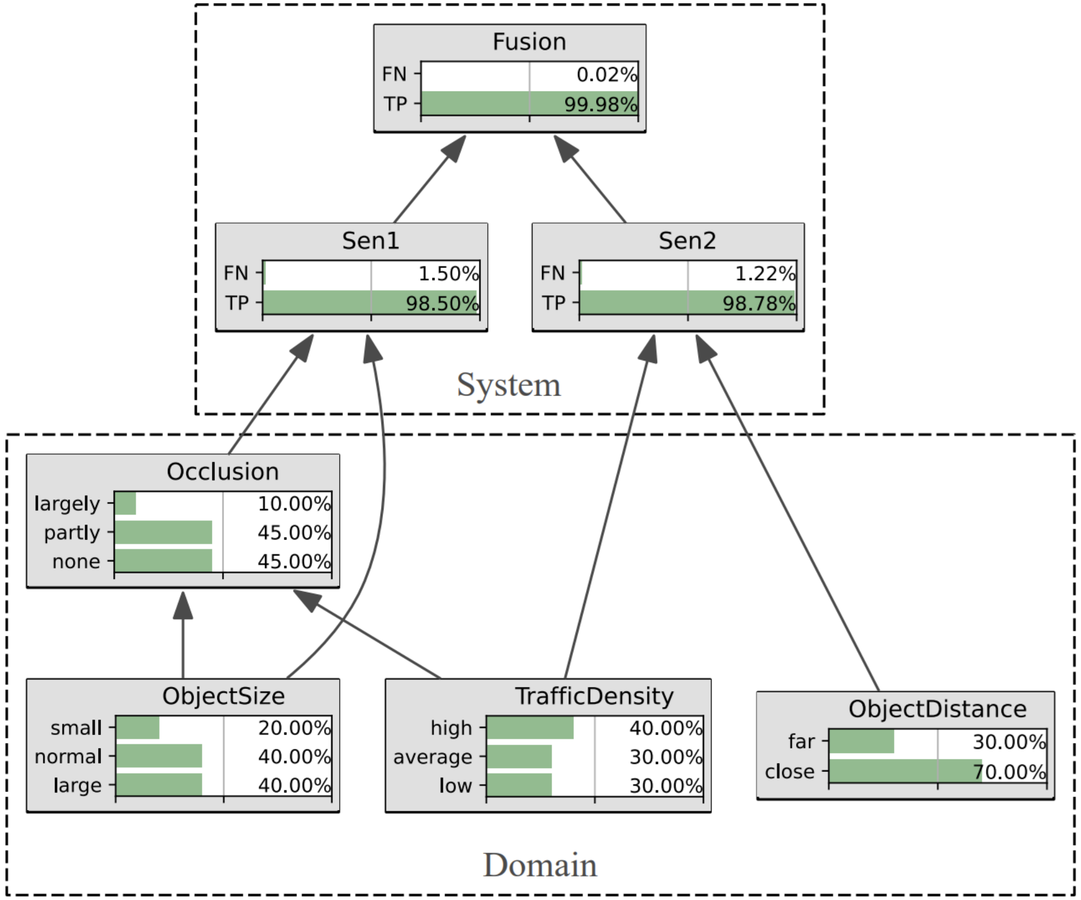


Causal Safety Analysis
Fault Trees vs. Causal Bayesian Networks

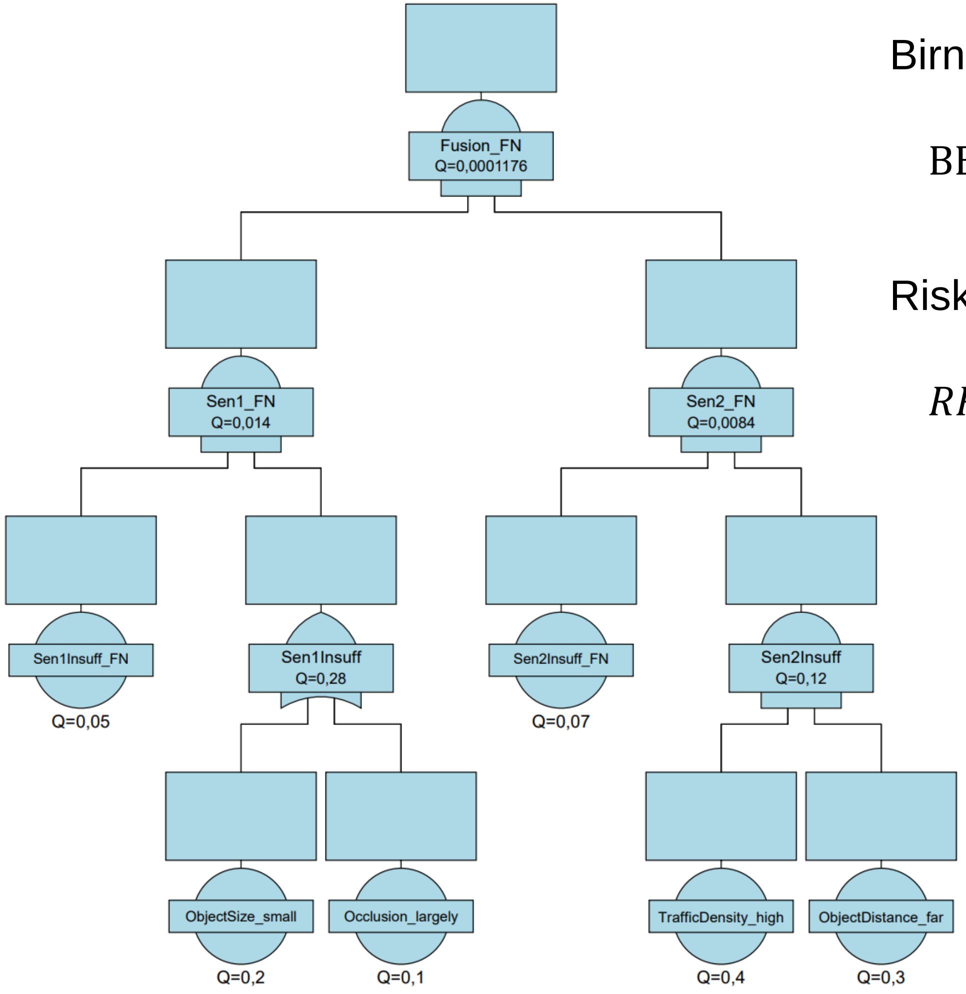
Fault Tree



Causal Bayesian Network



Causal Safety Analysis
Importance Metrics



Fault Tree

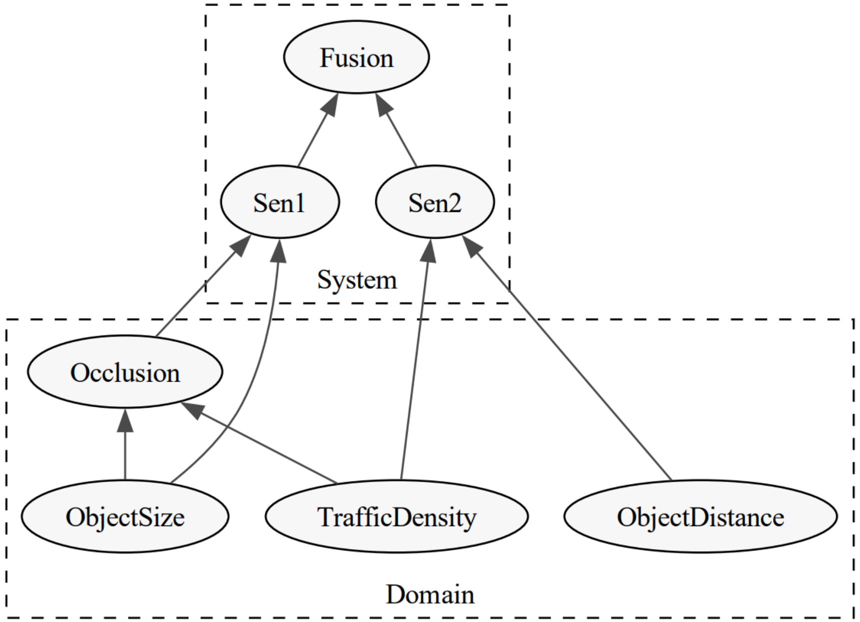
Birnbaum Importance:

$$\mathrm{BB} = \frac{\partial P(T = fail)}{\partial P(N_i = fail)}$$

Risk Reduction Worth:

$$RRW = \frac{P(T = fail)}{P(T = fail|N_i = \neg fail)}$$

Causal Safety Analysis
Importance Metrics



Fault Tree	Causal Bayesian Network

Birnbaum Importance:

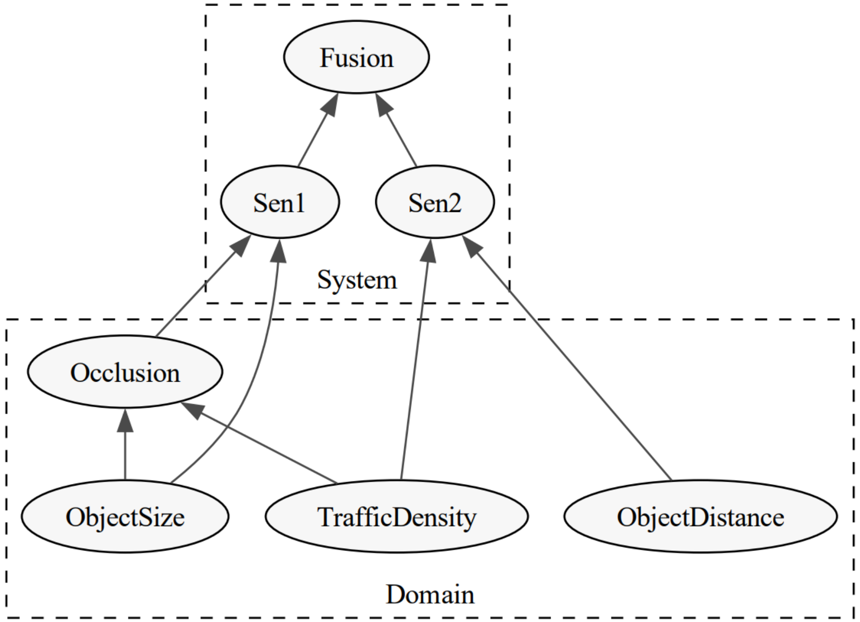
$$BB = \frac{\partial P(T = fail)}{\partial P(N_i = fail)} \qquad BB = \frac{\partial P(Y)}{\partial P(X = x)}$$

Risk Reduction Worth:

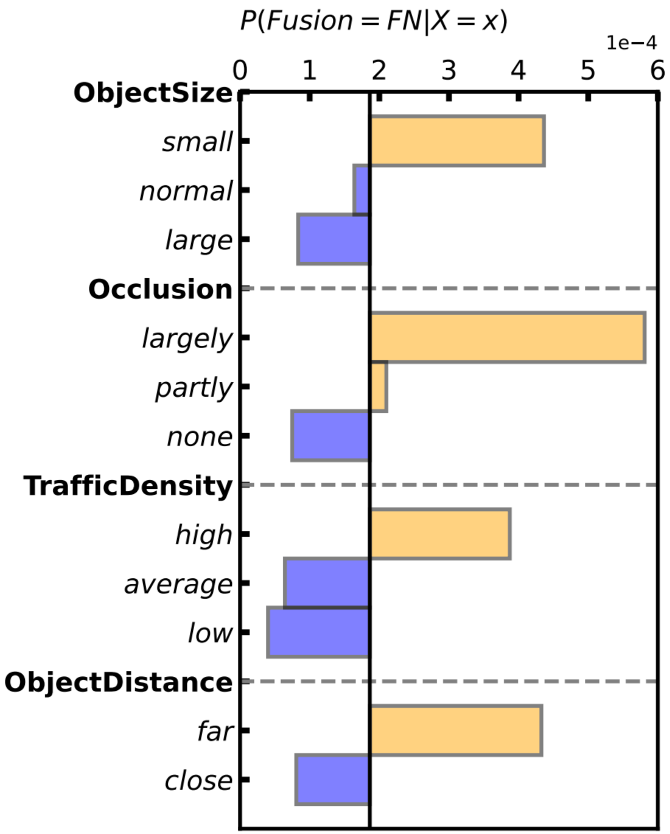
$$RRW = \frac{P(T = fail)}{P(T = fail | N_i = \neg fail)} \qquad RRW = \frac{P(Y)}{P(Y | X = x_{ref})}$$

Triggering Condition	**BB** $(^{*}10^{-4})$		**RRW**	
	FTA	CBN	FTA	CBN
Object Size	3.78	3.12	2.80	1.50
Occlusion	3.36	4.39	1.40	1.33
Traffic Density	2.94	3.35	∞	3.59
Object Distance	3.92	3.52	∞	2.31

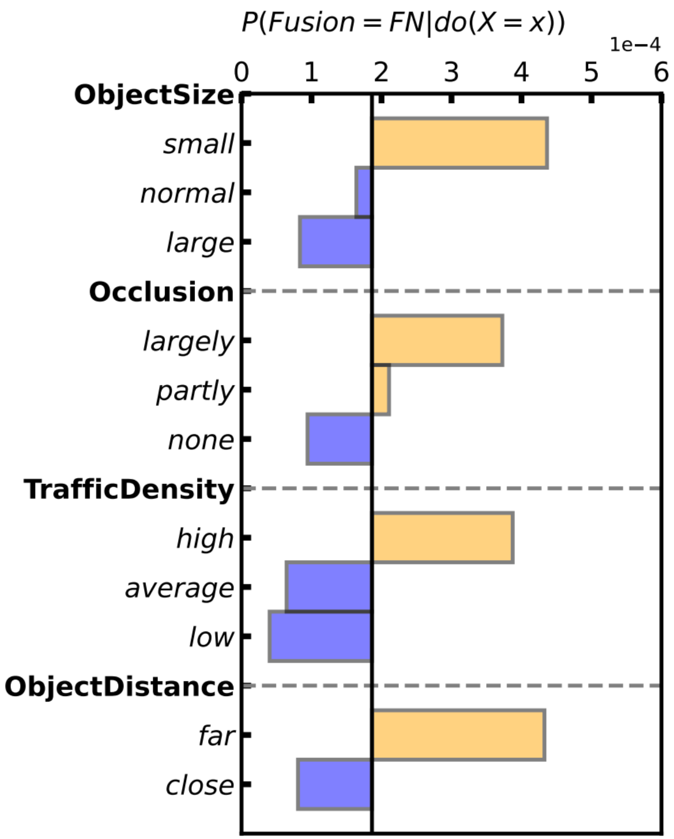
Causal Safety Analysis
Importance Metrics



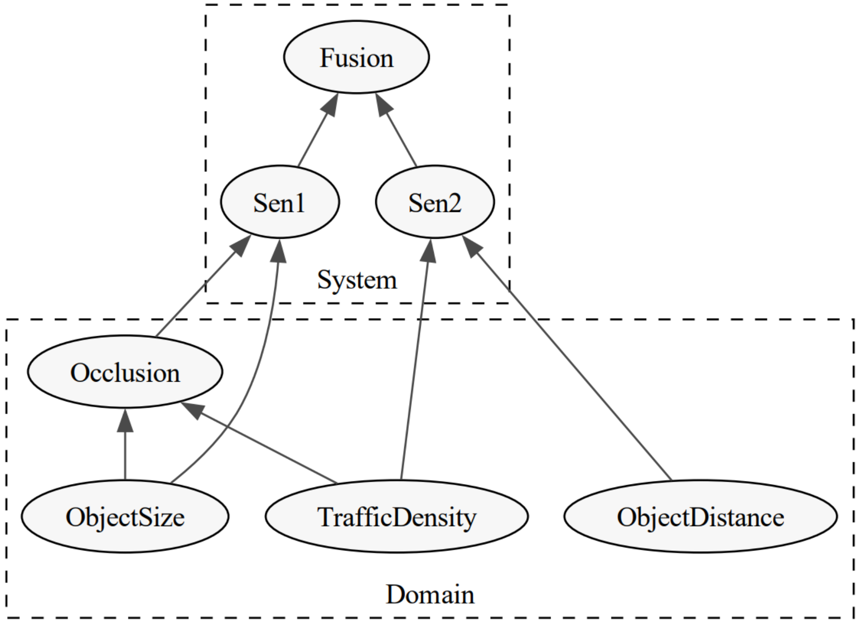
Correlation



Causation



Causal Safety Analysis
Importance Metrics



Correlation

Birnbaum Importance:

$$BB = \frac{\partial P(Y)}{\partial P(X = x)}$$

Risk Reduction Worth:

$$RRW = \frac{P(Y)}{P(Y|X = x_{ref})}$$

Causation

Average Causal Effect:

$$ACE = P(Y|do(X = x)) - P(Y|do(X = x_{ref}))$$

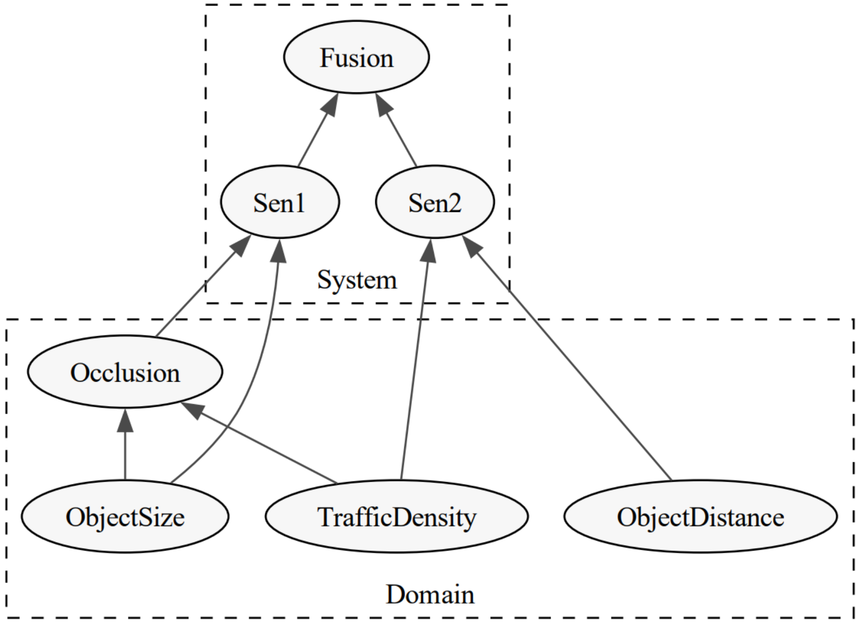
Relative Causal Effect:

$$RCE = \frac{P(Y|do(X = x))}{P(Y|do(X = x_{ref}))}$$

Interventional Risk Reduction Worth:

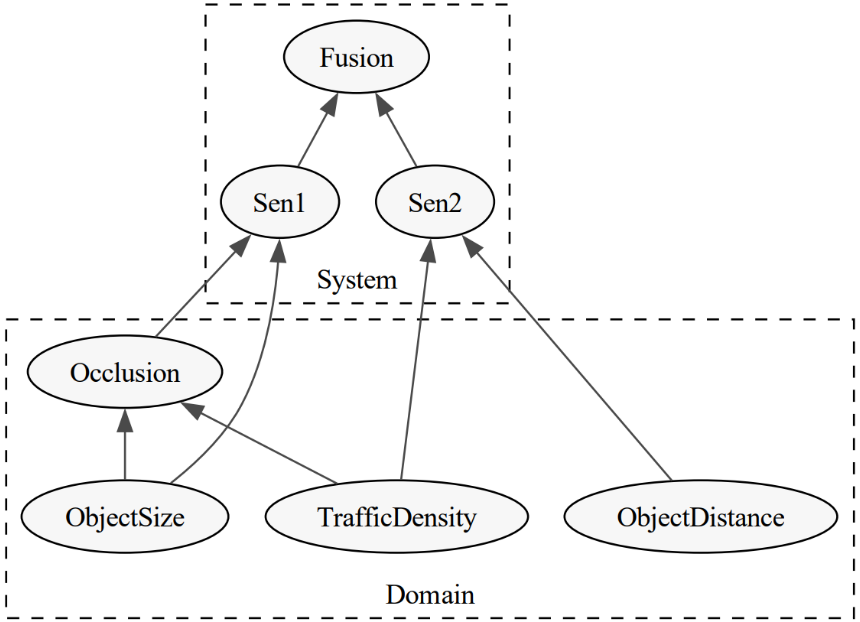
$$IRRW = \frac{P(Y)}{P(Y|do(X = x_{ref}))}$$

Causal Safety Analysis
Importance Metrics



Triggering Condition	State	RCE	RRW	IRRW
Object Size	small	2.66	1.14	1.14
	normal	1.00		
	large	0.51		
Occlusion	largely	3.95	2.49	1.97
	partly	2.23		
	none	1.00		
Traffic Density	high	9.64	4.64	4.64
	average	1.64		
	low	1.00		
Object Distance	far	5.36	2.31	2.31
	close	1.00		

Causal Safety Analysis
Importance Metrics

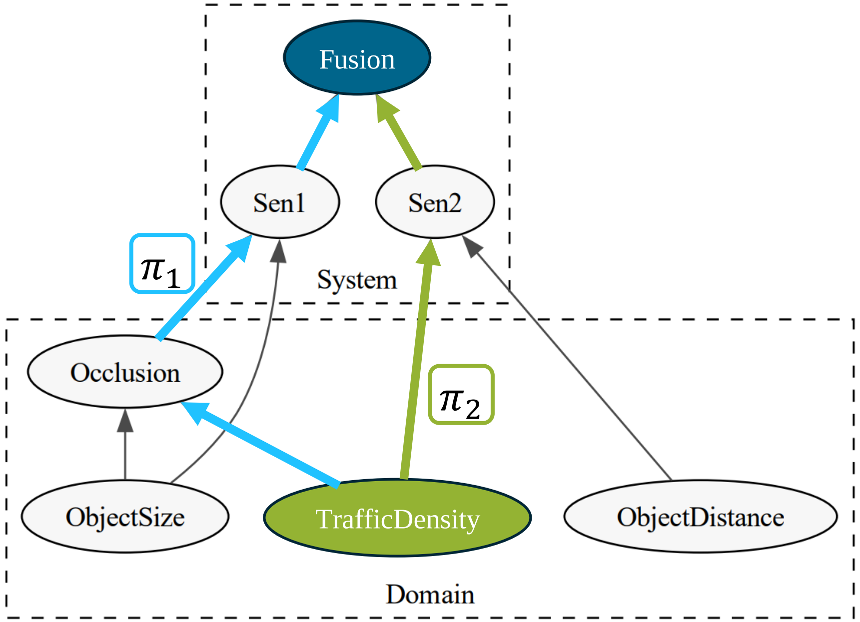


Multiple Interventions

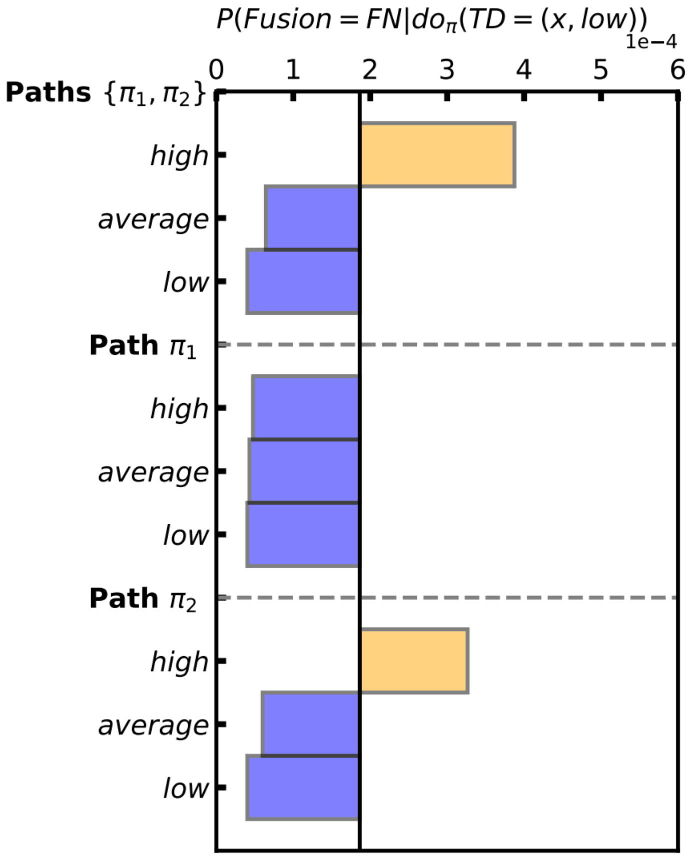
$$RCE_C^2 = \frac{P(Y|do(X_1 = x_1, X_2 = x_2))}{P(Y|do(X_1 = x_{1,ref}, X_2 = x_{2,ref}))}$$

		ObjectSize			Occlusion			TrafficDensity			ObjectDistance	
		small	normal	large	largely	partly	none	high	average	low	far	close
ObjectSize	small				9.72	7.86	4.92	26.42	4.87	2.98	14.34	2.75
	normal				5.90	2.96	1.00	10.23	1.56	1.00	5.48	1.00
	large				4.92	1.98	0.51	5.24	0.77	0.48	2.80	0.50
Occlusion	largely	9.72	5.90	4.92				32.10	5.91	3.95	20.31	3.95
	partly	7.86	2.96	1.98				18.16	3.34	2.23	11.49	2.23
	none	4.92	1.00	0.51				8.13	1.50	1.00	5.14	1.00
TrafficDensity	high	26.42	10.23	5.24	32.10	18.16	8.13				23.02	2.91
	average	4.87	1.56	0.77	5.91	3.34	1.50				1.85	1.33
	low	2.98	1.00	0.48	3.95	2.23	1.00				0.76	1.00
ObjectDistance	far	14.34	5.48	2.80	20.31	11.49	5.14	23.02	1.85	0.76		
	close	2.75	1.00	0.50	3.95	2.23	1.00	2.91	1.33	1.00		

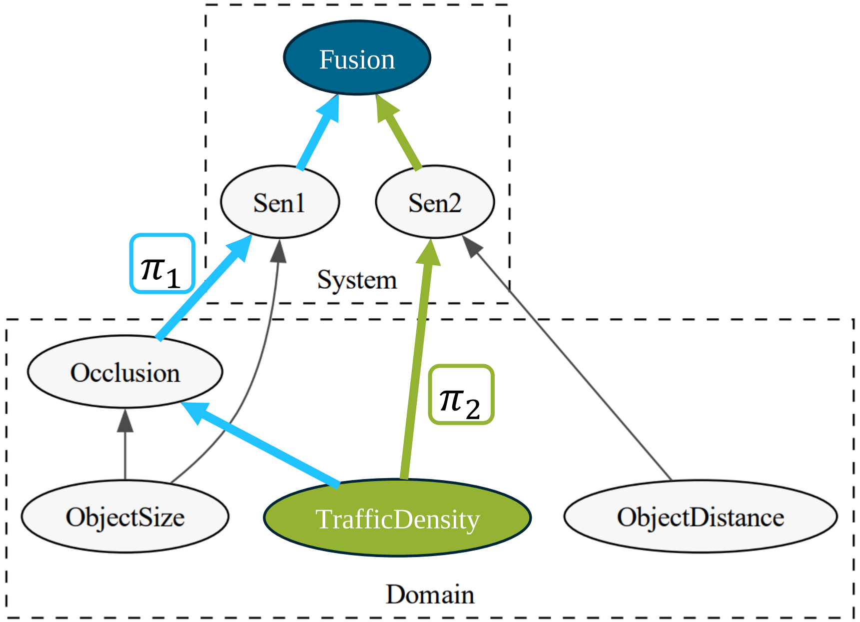
Causal Safety Analysis
Importance Metrics



Path-Specific Effects



Causal Safety Analysis
Importance Metrics



Path-Specific Effects

Average Path-specific Effect:

$$APE = P(Y|do_{\pi}(X = (x, x_{ref}))) - P(Y|do(X = x_{ref}))$$

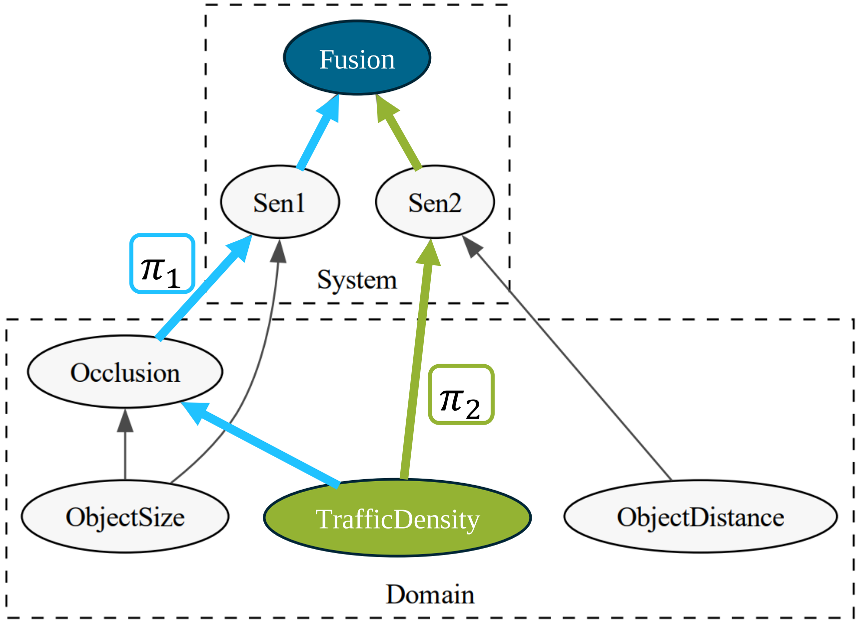
Relative Path-specific Effect:

$$RPE = \frac{P(Y|do_{\pi}(X = (x, x_{ref})))}{P(Y|do(X = x_{ref}))}$$

Ratio APE and ACE:

$$\frac{APE}{ACE} = \frac{P(Y|do_{\pi}(X = (x, x_{ref}))) - P(Y|do(X = x_{ref}))}{P(Y|do(X = x)) - P(Y|do\big(X = x_{ref}\big))}$$

Causal Safety Analysis
Importance Metrics



Path-Specific Effects

Path	Traffic Density State	APE ($^*10^{-4}$)	RPE	$\frac{APE}{ACE}$
π_1	high	0.08	1.19	0.02
	average	0.03	1.07	0.12
	low	0.00	1.00	-
π_2	high	2.86	8.13	0.82
	average	0.20	1.50	0.82
	low	0.00	1.00	-

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Causal Bayesian Networks enable…

- modelling relations of complex systems operating in open environments
- integration of data-driven and expert-based knowledge
- quantitative assessment of causal influences

⇒ evaluation of fault and failure propagation leading to harm

Challenges:

- Substantial data required to capture rare events
- Expert-based modelling of causal graphs
- Verification of causal Bayesian networks

Thank you for the attention.

Contact:

Lina Putze, M.Sc.

German Aerospace Center (DLR) e.V.

Institute of Systems Engineering for Future Mobility

lina.putze@dlr.de