

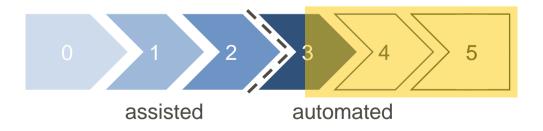
Motivation



Automated Driving (AD)

- brings ...
 - safety
 - efficiency
 - availability
 - comfort

SAE levels for AD



Challenges

- Data amounts
 - \sim 10 TB/h for AD \rightarrow \sim 10 ZB to release
- Open Context
 - What is relevant?





Agenda



State of the art **Research Questions Data Reduction** Relevance Method **Evaluation** ? Results Outlook



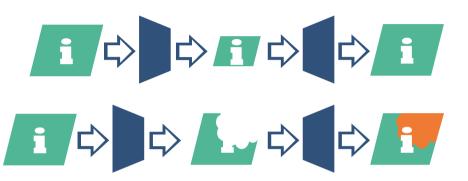
State of the art



Data reduction for AD

Lossy or Lossless

- **Low-Level features**
 - e.g. Pixel
 - Technology far advanced
- **High-Level features**
 - Simple methods (Triggering)
 - Missing use of domain knowledge for AD























Research Questions



1. How can the open context present in automated driving be addressed in data reduction?

2. How can relevance be formally defined to facilitate its use in data reduction?

3. What is the impact of this data reduction method on the performance of subsequent use cases?



















Relevance: Method

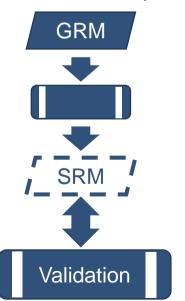


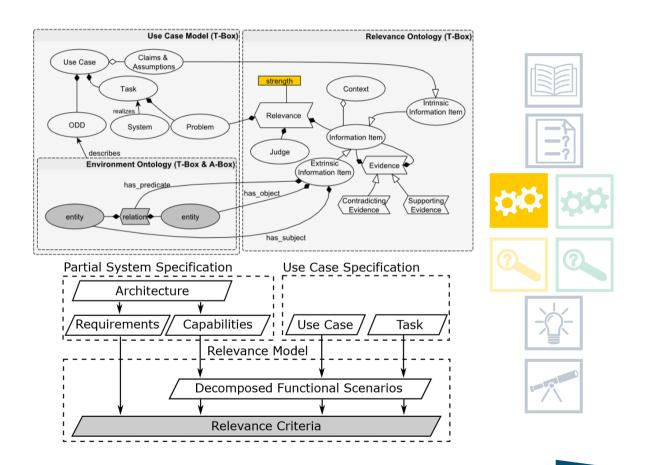
General Relevance Model (GRM)

Abstract description using ontologies

Specific Relevance Model (SRM)

Use Case specific implementation details



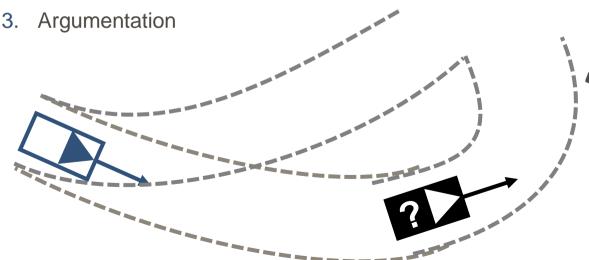


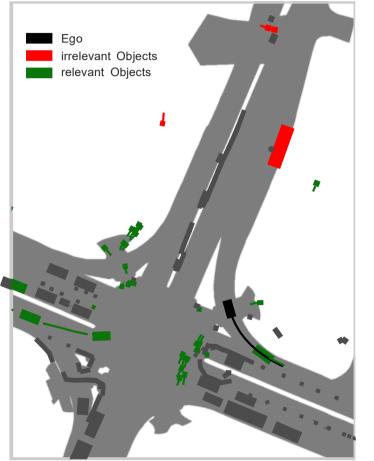
Relevance: Method



Proof of Concept

- Perception relevance for collision free driving
- Three principles
 - 1. Worst-Case assumption
 - 2. Superposition















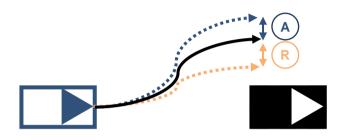






Relevance: Evaluation

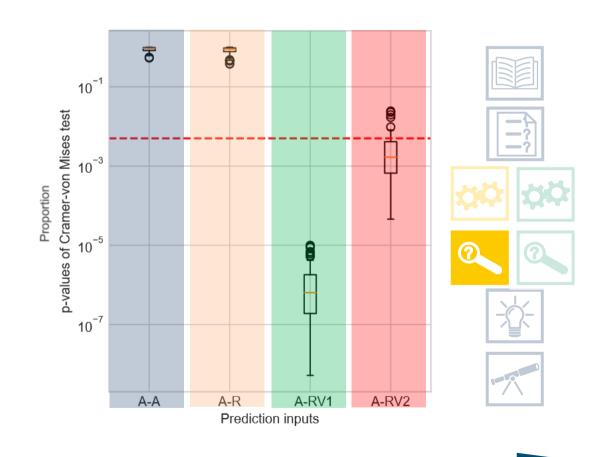




Validation Concept

- Reference: human driver
- Compare Ego prediction with different information
- Aggregation of prediction errors
- Cramer-von Mises Test:



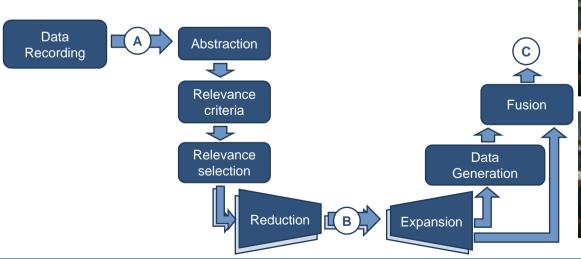


Data Reduction: Method



Concept

- Reduction by abstraction
- Expansion by "plausible lie"
- Relevant information left unaltered

















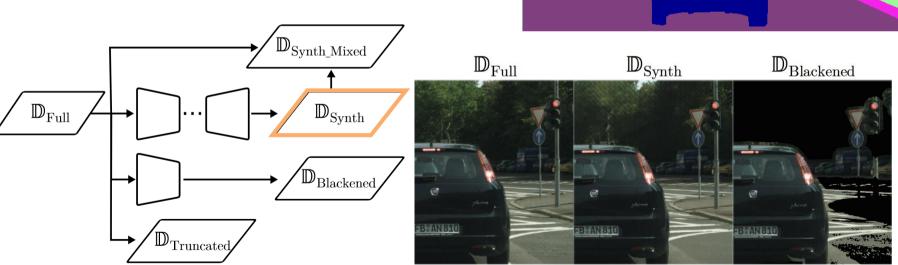




Data Reduction: Evaluation



- Impact on Neural Nets
 - Inference | Training
 - Object detection | Semantic segmentation
- 5 datasets for evaluation

















Data Reduction: Evaluation



Inference

- Proposed method D_{Synth}:
 - Small impact on performance
- Alternative method D_{Blackened}:
 - Large impact on performance

→ "Plausible lie" of irrelevant information essential for inferenz

Semantic segmentation (mIoU)



	\mathbb{D}_{Full}	\mathbb{D}_{Synth}	$\mathbb{D}_{Blackened}$
Relevant Ø	0,823	0,819	0,37
Irrelevant Ø	0,79	> 0,72	-
Ø	0,81	0,78	-

















Object detection (mAP₅₀)



	\mathbb{D}_{Full}	\mathbb{D}_{Synth}	$\mathbb{D}_{Blackened}$
Relevant Ø	0,373	0,369	0,14

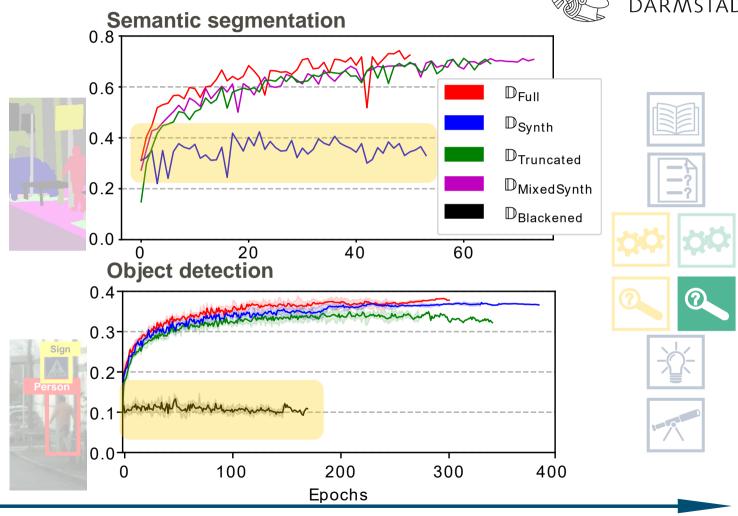
Data Reduction: Evaluation

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Training

- X Semantic segmentation
- ✓ Object detection
- → Dependent on Use Case

→ "Plausible lie" of irrelevant informatio essential for training



Results

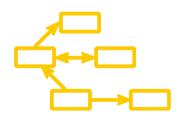






Inclusion of domain-specific relevance

- → Control of information losses
- → Effective management of performance losses



2. Description of relevance?

Ontological models

- → Adaptive modeling for different relevance concepts
- → Derivation of relevance from knowledge representation



3. Impact on performance?

- → Suitability for inference and training of neural networks
- → Dependence on the use case

















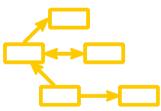
Outlook





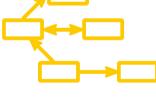


- Common representation of various sensor modalities
- Enhanced understanding of use case dependency



Relevance modeling

- Establishment of differentiated relevance consideration in AD
- Standardized concepts and nomenclature for relevance in AD



Application

- Previously "laboratory conditions"
- Possible application modes?
- Transferability/scaling to industrial application?

























Thank you

Kai Storms

Funded by:





