The Power of AI & CV for Automation in Rail and its Challenges

Claus Bahlmann

EDCC – 2021/09/14

This presentation is about

1

Why Automation in Rail needs AI?

2

What AI based Automation Exist in Rail?

3

How to develop enterprise grade AI for Automation in Rail?

What are the key challenges for AI based Automation in Rail?

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Why Automation in Rail needs AI?

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Why Automation in Rail needs AI?

Why Automation in Rail needs AI?

Infrastructure defects
Train defects
Lack of drivers
Delays
Wait times on platform

Boarding issues

Passenger experience

NÜRNBERG 02.04.2019

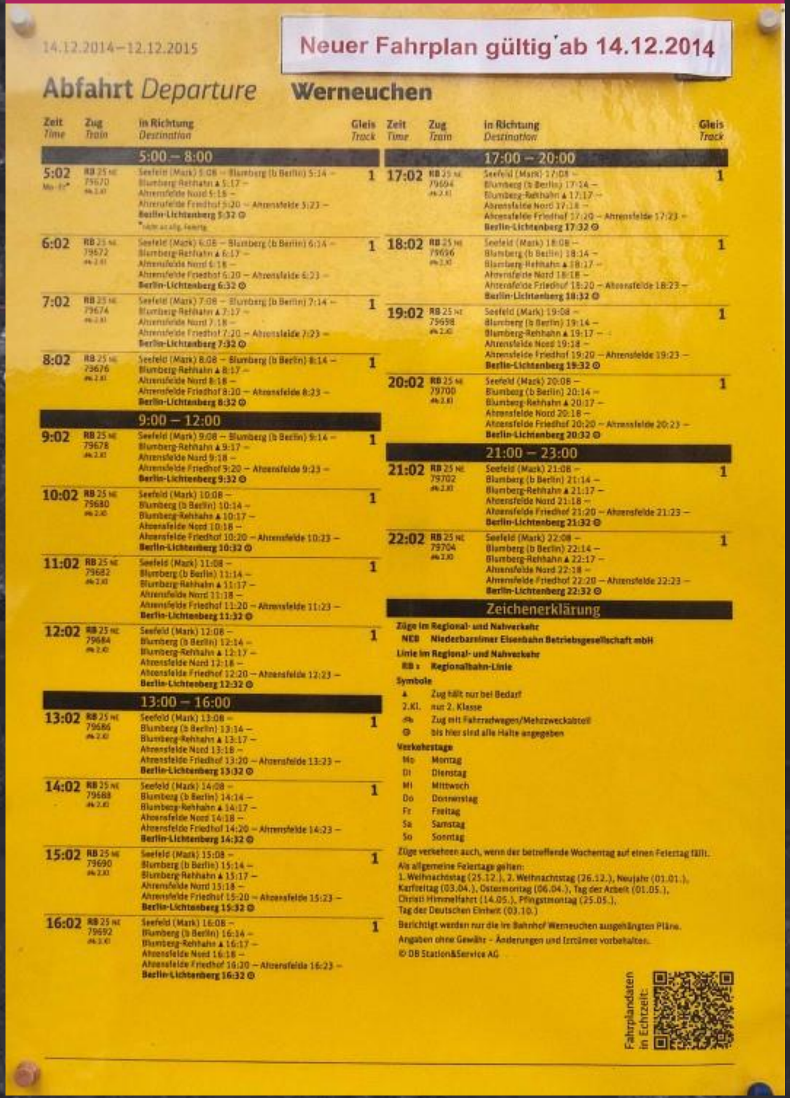
Großeinsatz

Messer-Mann (23) bedroht Fahrgäste in Nürnberger U-Bahn - Polizei rückt an

In der U-Bahn in Nürnberg hat ein offenbar geistig verwirrter Mann Fahrgäste mit einem Messer bedroht. Als die Polizei eintraf, drohte er auch den Beamten mit seiner Waffe.

Wegen Corona: Millionen Fahrgäste bleiben Bussen und Bahnen fern

Sparse timetables



S S-Bahn U U-Bahn Tram Bus F Fähre

04:00

Why Automation in Rail needs AI?

Intelligent automation is needed to tackle current shortcomings in transportation

Improve rail system availability through
just-in-time maintenance

Optimize rail system life cycle through
building and exploitation of digital twins

Improve passenger throughput, energy and cost efficiency through
highly automated operation

Improve passenger experience through
flexible and demand responsive, driverless operation

S S-Bahn U U-Bahn Tram Bus F Fähre

04:00

What AI based Automation Exist in Rail?

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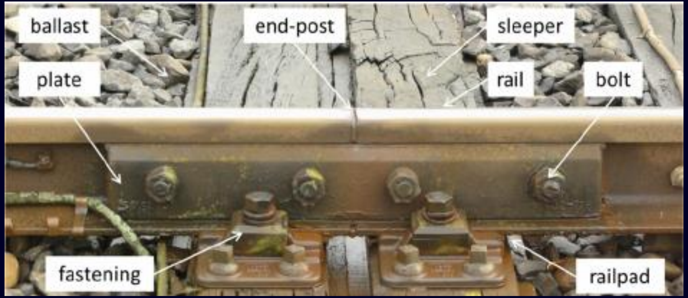
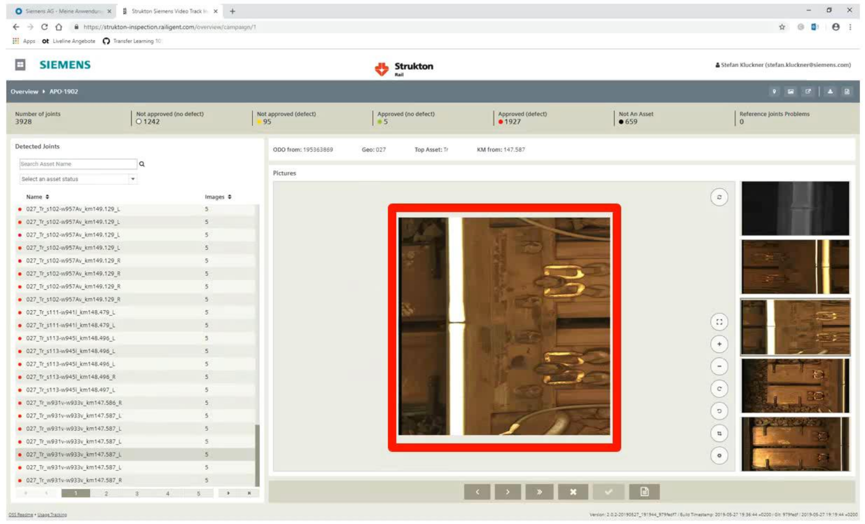
Railigent® Video Track Inspector
AI for automated rail inspection





Asset has defects

USE CASE

- Towards 100% rail infrastructure availability, while allowing for substantial cost savings and higher reliability
- Identification and detection of insulated rail joint defects
- Generate service work orders with information about location, level of urgency and tasks to be performed
- Extension to other asses planned, e.g., switches, fishplates, …
- Runs as service in Siemens Mobility Railigent® platform

TECHNOLOGY

- Multi-linescan camera system attached to video surveillance train
- Algorithm 1: Visual detection and localization of rail joints
- Algorithm 2: Visual inspection of rail joint condition (e.g., gap closure)
- Additional AI features can be deployed via the implemented self learning concept with expert-in-the-loop
- Computer Vision powered by Siemens Mobility Deep Learning Factory

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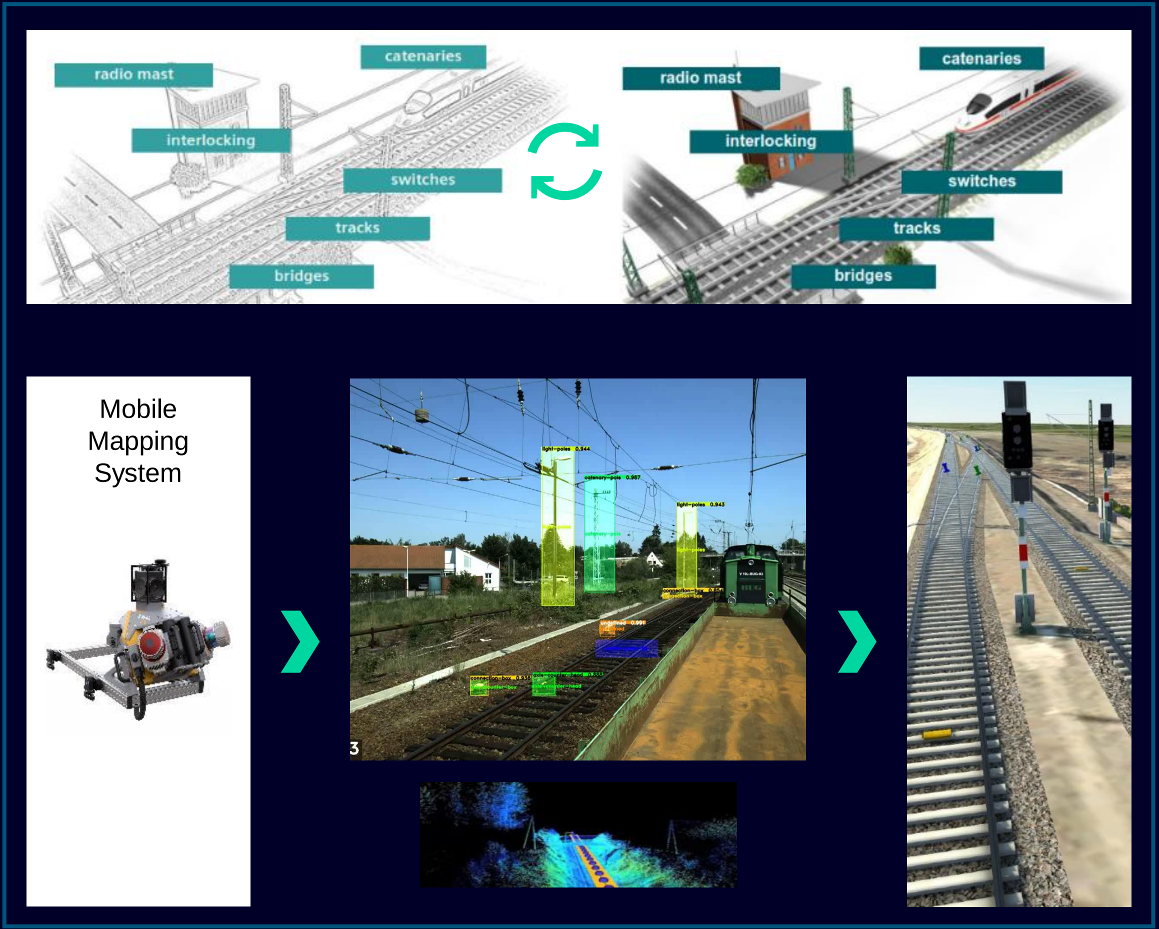
Digital Infrastructure Twin & BIM[1]

Automation of digital site surveys with intelligent sensor analytics



USE CASE

- Automation of digital site surveys and creation of BIM representations
- Assist condition monitoring and predictive maintenance of assets & vegetation
- Localization through re-ID of landmarks (“virtual balises”)
- Digital Maps for the Rail Industry

TECHNOLOGY

- Mobile mapping system
- Automatic recognition of infrastructure elements: e.g., signs, signals, tracks, switches, balises, masts, bridges, etc.
- Use of geometry to recover an asset’s 3D location, add GPS information to locate an asset in the real world
- Perform Optical Character Recognition (OCR) to extract textual information
- Integration with existing BIM workflow (e.g., Bentley, Autodesk, …)
- Computer Vision powered by Siemens Mobility Deep Learning Factory

[1]BIM = Building Information Modeling

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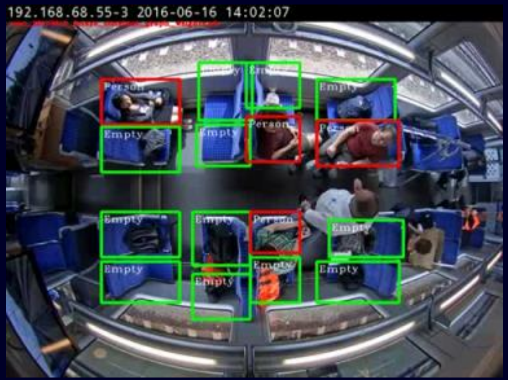
iCCTV
Intelligent Functions for CCTV Analytics

Extension of the classical CCTV systems through intelligent video analytics functions for improved passenger safety and comfort

Use cases are being piloted. More use cases under development…

Seat Occupancy Recognition – per seat and distinguishing person/luggae



Wheel-Chair Area usage detection – Distinguish person/wheelchair

Automated aggression detection – Detect and warn authorities

Passenger Counting

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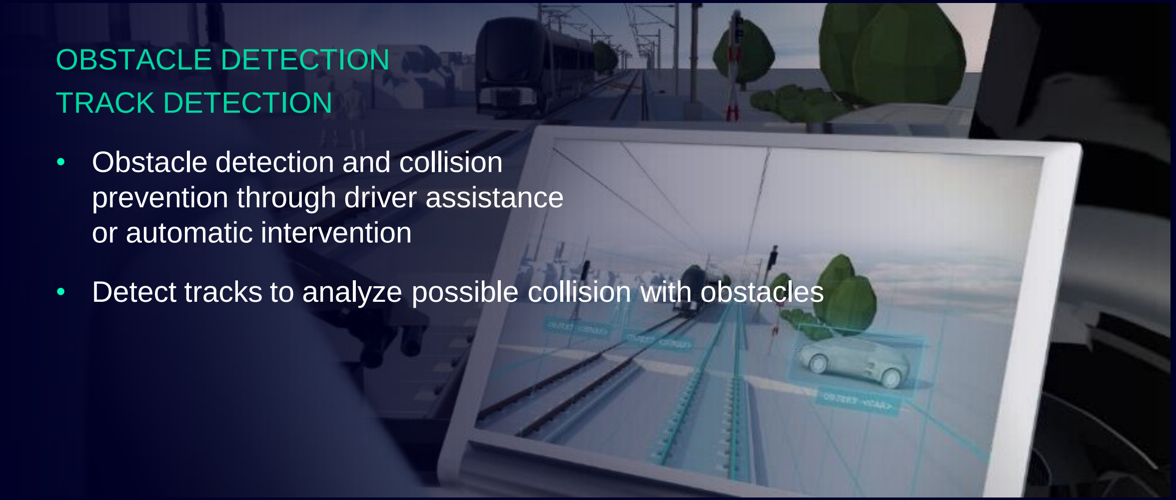
Assisted and Unattended Driving in Rail – Grade of Automation 3/4



OBSTACLE DETECTION
TRACK DETECTION

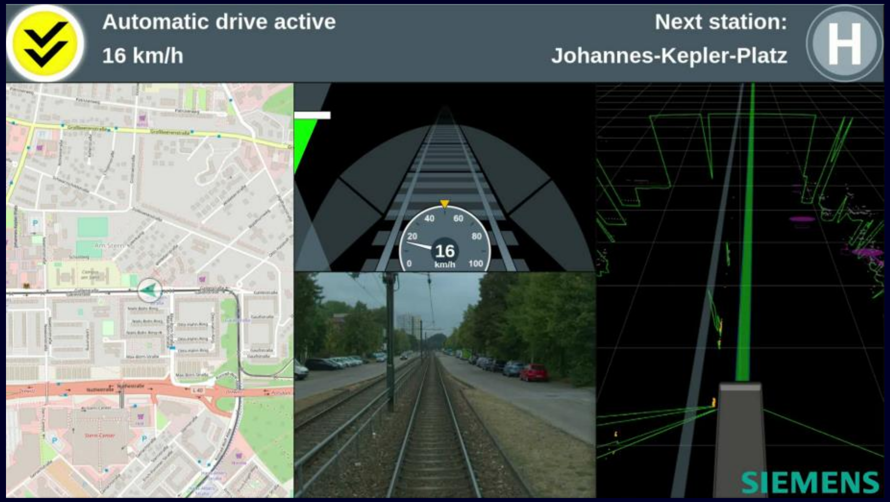
- Obstacle detection and collision prevention through driver assistance or automatic intervention
- Detect tracks to analyze possible collision with obstacles

SIGNAL RECOGNITION

- Timely perception of signals to support driver for automated intervention
- Allowing energy-optimized operation
- Relevant in non-ETCS scenarios

AUTONOMOUS TRAM

- Research project of the world’s first autonomous tram presented at InnoTrans 2018
- Powered by multiple sensors & AI
- Tram responds to trackside tram signals, stops at tram stops, and reacts autonomously to hazards such as crossing pedestrians and other vehicles
- Cooperation with ViP (Potsdam)



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How to develop enterprise grade AI for Automation in Rail?

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Deep Learning Factory

Workflow, Marketplace, Blueprints & Expert Community for CV & DL in Mobility

Benefits: Lower cost & higher speed, efficiency and quality in development of CV & DL product functions

Data

Deep Learning Factory (DLF)

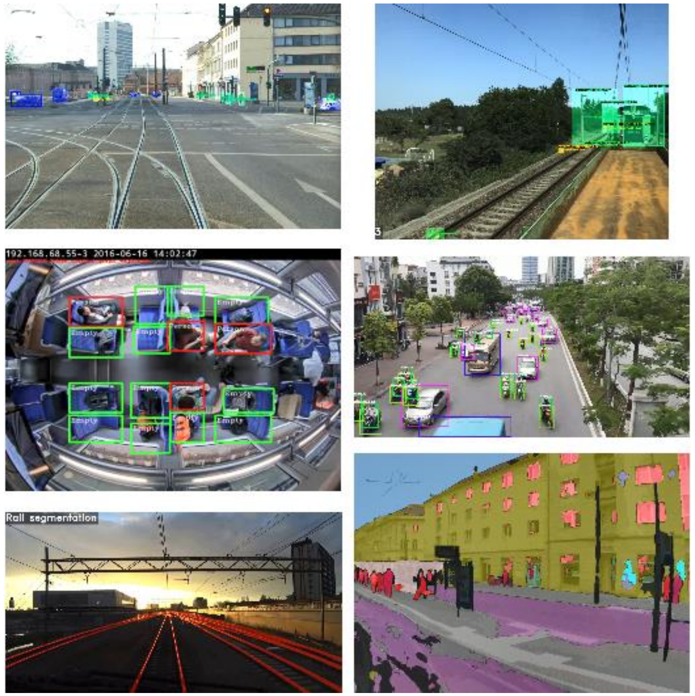
DL Modules & Workflow: A set of common tools with well defined interfaces allow creating typical AI/DL modules and gluing them into DL workflows

ai.store: An internal marketplace for publishing, retrieving and sharing data, DL models, trainings, results and experiments

Use cases & Blueprints: Gluing & tuning of DL pipelines that solve for prototypical templates and specific use case requirements

Expert Community: Diverse team of AI, DL, CV, SW, data & agile experts

Product functions



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Deep Learning Factory
Workflow, Marketplace, Blueprints & Expert Community for CV & DL in Mobility

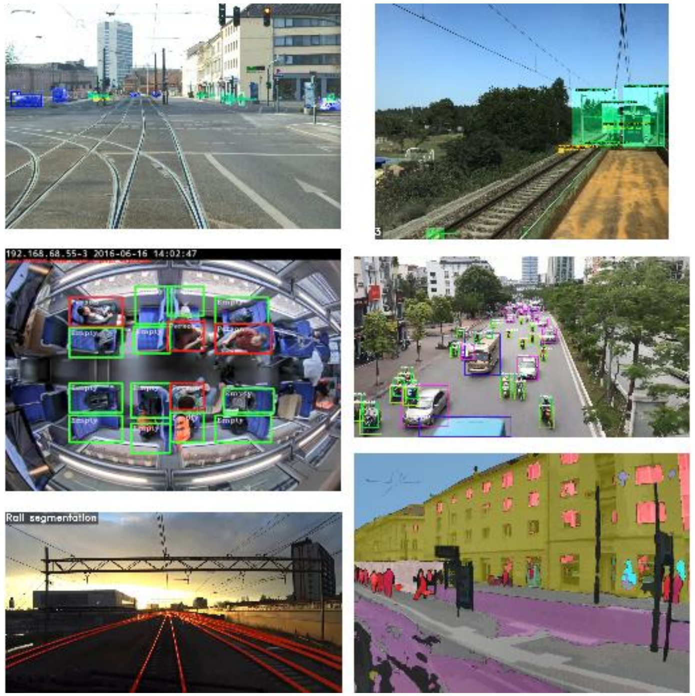
Benefits: Lower cost & higher speed, efficiency and quality in development of CV & DL product functions

Data

Deep Learning Factory (DLF)

- **DL Modules & Workflow** → Modularity & Reusability
- **ai.store** → Reproducibility, Traceability & Collaboration
- **Use cases & Blueprints** → Development Efficiency
- **Expert Community** → Technology Excellence

Product functions



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Deep Learning Factory
Use Case – Image Object Detection

Signal detection – Lightrail

Signal detection – Mainline

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Deep Learning Factory
Use Case – Image Object Detection

Road user detection in Lightrail environment

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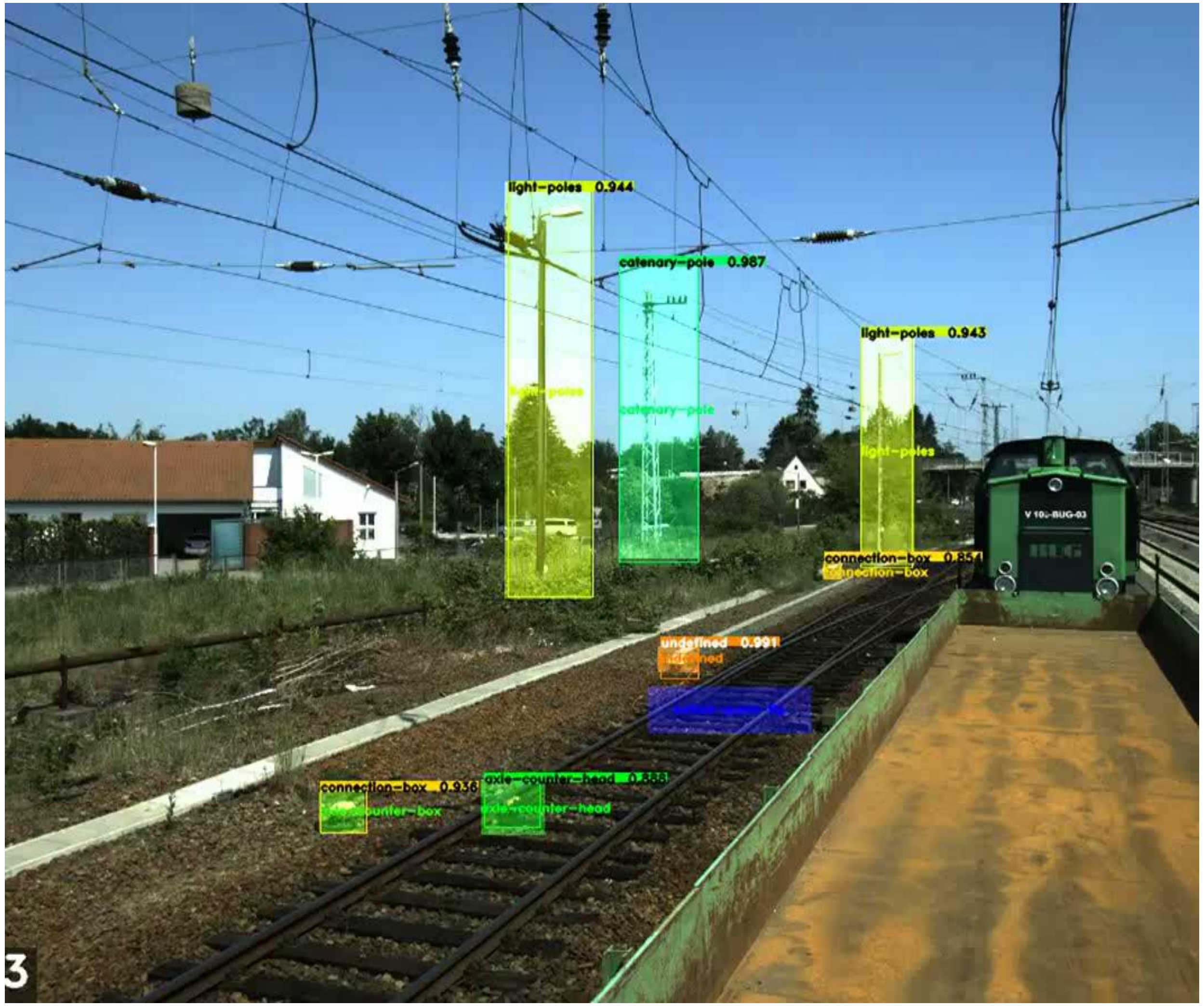
Deep Learning Factory
Use Case – Image Object Detection



Infrastructure element detection

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Deep Learning Factory
Use Case – Image Object Segmentation

Input | Track bed overlay | Track bed | Tracks

Track segmentation

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What are the key challenges for AI based Automation in Rail?

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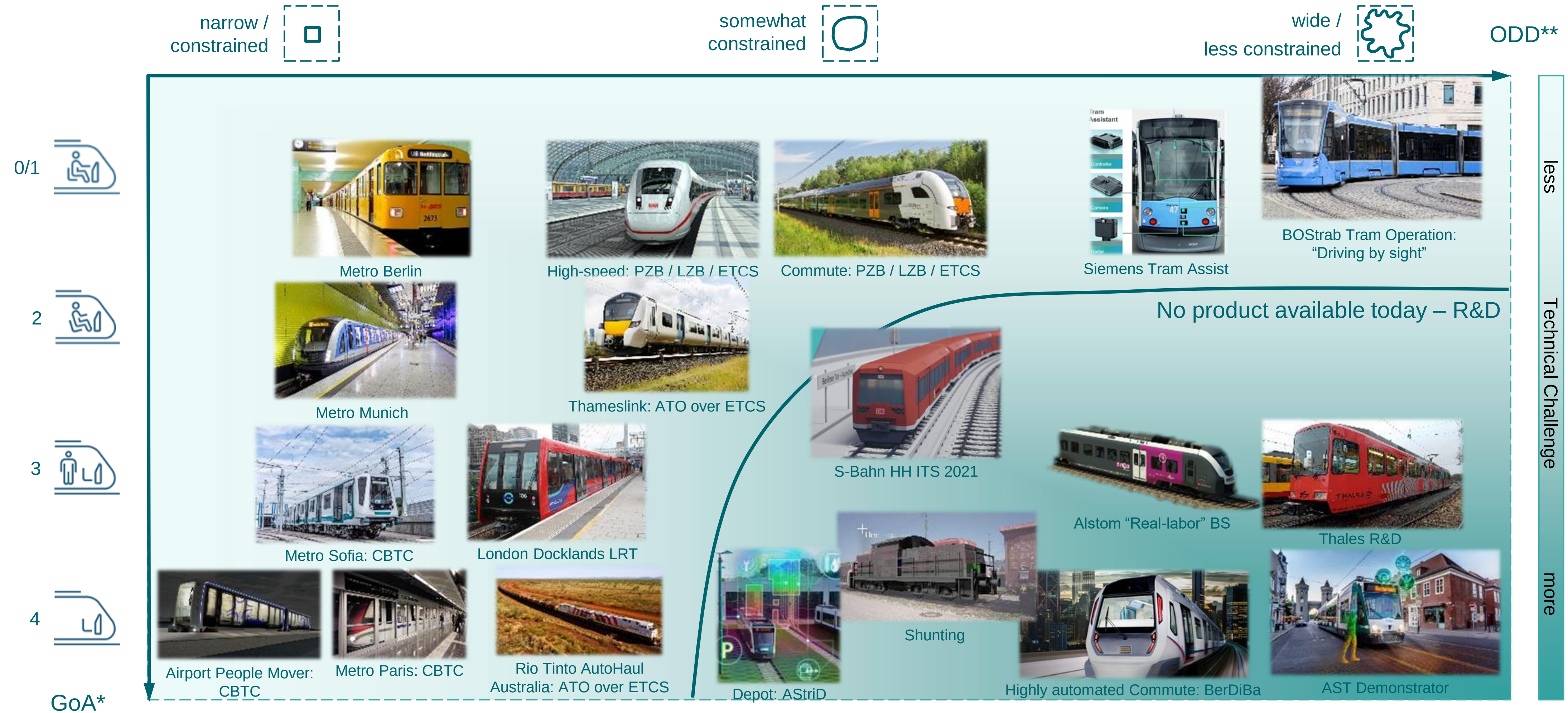
Highly Automated and Driverless Driving in Rail



*GoA = Grade of Automation (IEC 62290)

**ODD = Operational Design Domain = Operation conditions under which an autonomous system is specifically designed to function

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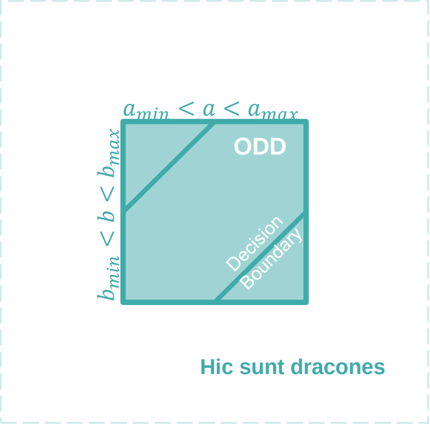
ODDs for Automated Driving in Rail and their Challenges

Narrow ODD in Rail

✓



Why?

- Many “Narrow ODD” business cases exist
- Narrow ODD can often be specified and solved with (comparably) simple, technology, allowing for (comparably) straightforward homologation and safety

How?

- Based on simple, but effective infrastructure rooted sensors, measures and logic e.g., balises, fences, doors, radar curtains, and ATP systems (PZB, LZB, ETCS, …), with (comparably) simple logic
- Often close the system to rail traffic, eliminating interaction with cars, people, …

Challenges

- Sometimes high costs
- Approaches cannot easily scale to wide ODDs, since the open world is complex

Wide / unconstrained ODD in Rail

Needs

Why?

- Also “Wide ODD” business cases exist and are not solved yet
- Traditional technology is not sufficient, especially when open world system (i.e., interaction with pedestrian, cars, …) is in scope

How?

- Wide ODD often cannot be specified by logic & rules → Instead, use data samples
- Learn ODD boundaries and state space decision boundaries using AI / ML
- Nevertheless, constrain ODD as much as possible, to allow for safe operation
- Combine with traditional Rail safety technology, where possible

Challenges

- Needs safe and trustworthy technology & homologation ecosystem for AI / ML → still in research phase

Needs Reliable, Safe & Trustworthy

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AI for Highly Automated Systems
Is everything solved?

OPPORTUNITY

AI/Machine Learning achieves incredible **performance** and is seen essential for automation.

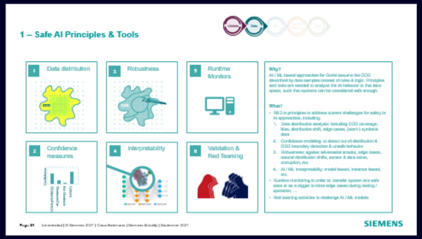
Today, AI/Machine Learning is not used in safety critical products, as it is hard to **verify**.

Huge opportunities arise from **Safe AI**

MEASURES TO BE ADDRESSED

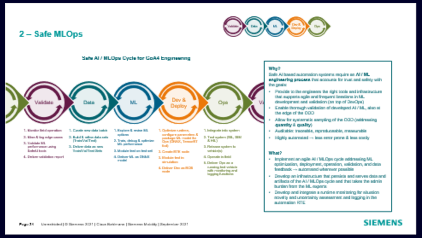
01 SAFE AI PRINCIPLES & TOOLS

Provide insight into AI/NN behavior and data distribution



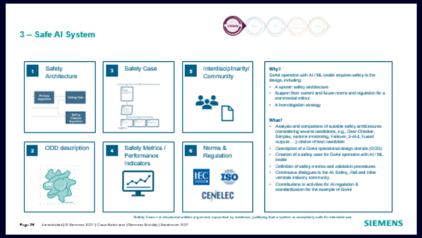
02 SAFE AI/MLOPS

Engineering environment for agile and large-scale development and validation



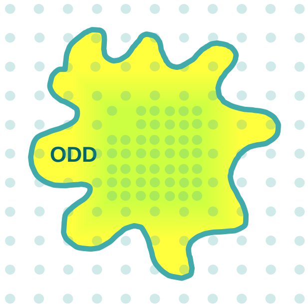
03 SAFE AI SYSTEM

Safety argumentation and regulatory framework for homologation

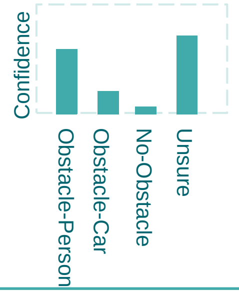


1 – Safe AI Principles & Tools

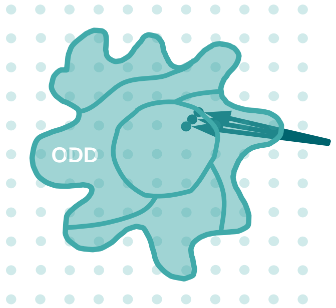
1 Data distribution



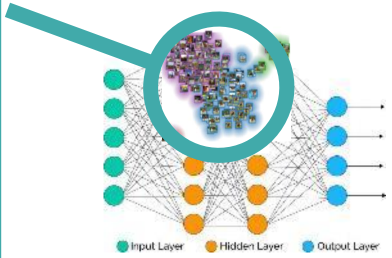
2 Confidence measures



3 Robustness

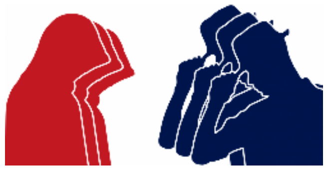


4 Interpretability



5 Runtime Monitors

6 Validation & Red Teaming



Why?

AI / ML based approaches for GoA4 assume the ODD described by data samples instead of rules & logic. Principles and tools are needed to analyze the AI behavior in this data space, such that systems can be considered safe enough.

What?

- R&D in principles to address current challenges for safety in AI approaches, including:
  1. Data distribution analysis: including ODD coverage, bias, distribution shift, edge cases, (semi-) synthetic data
  2. Confidence modeling: to detect out-of-distribution & ODD boundary detection & unsafe behavior
  3. Robustness: against adversarial attacks, edge cases, natural distribution shifts, sensor & data noise, corruption, etc.
  4. AI / ML Interpretability: model based, instance based, etc.
- Runtime monitoring in order to: transfer system into safe state or as a trigger to mine edge cases during testing / operation, …
- Red teaming activities to challenge AI / ML models

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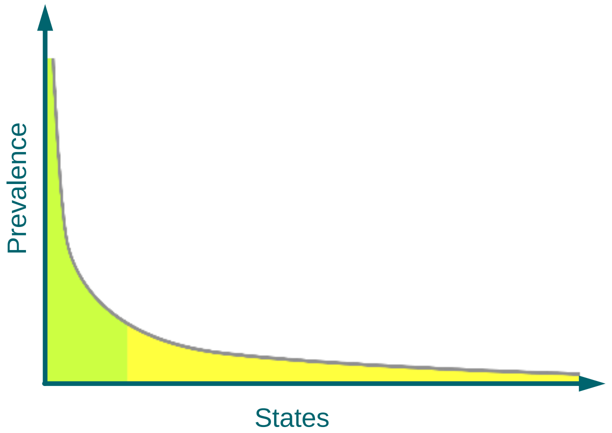
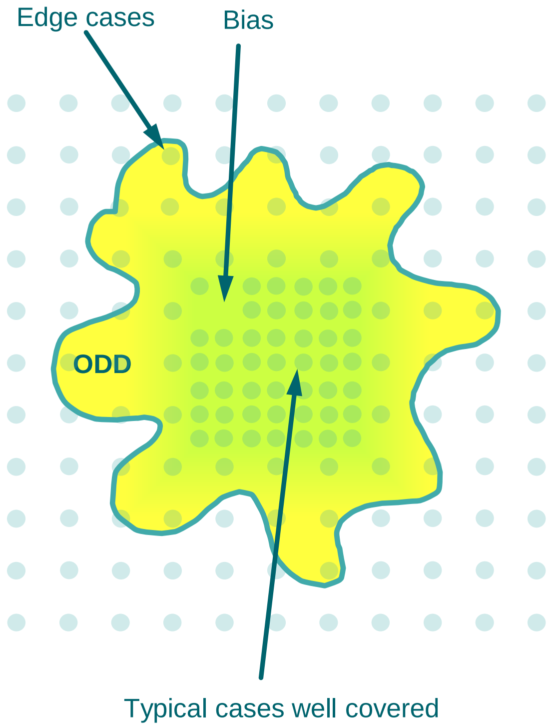
1 – Safe AI Principles & Tools





1 **Analyze data distribution**

Why?

- How well do we know our data?
- Data distributions are often governed by long tail?
- Sustainable training and validation of machine learning approaches requires systematic sampling of ODD
- Edge cases
  - Too rare to sample by chance for design of a system
  - Too prevalent to not hit them in 24/7 operation
- Bias
  - Systematic error in the sampling, e.g., due to unconscious assumptions
- Drift
  - Data characteristics might drift over time, e.g., due to seasons or

What?

- Careful analysis & visualization of collected data
- Edge case mining
- (Semi-) synthetic data generation
- …

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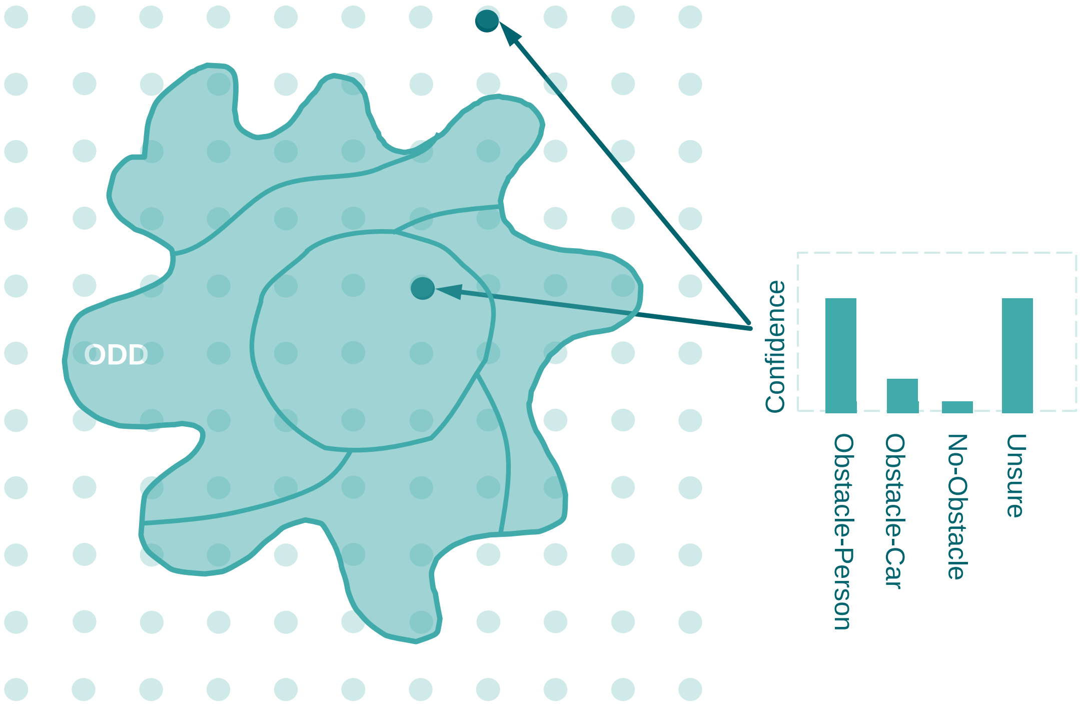
1 – Safe AI Principles & Tools



2 Confidence measures

Why?

- Confidences used in NN today (e.g., softmax) map rarely to probabilities
- Confidence values are mostly too confident
- Safe systems need detect out-of-distribution or “unsure” behavior for deploying fail-safe backups

What?

- Ensembles
- Monte carlo
- …

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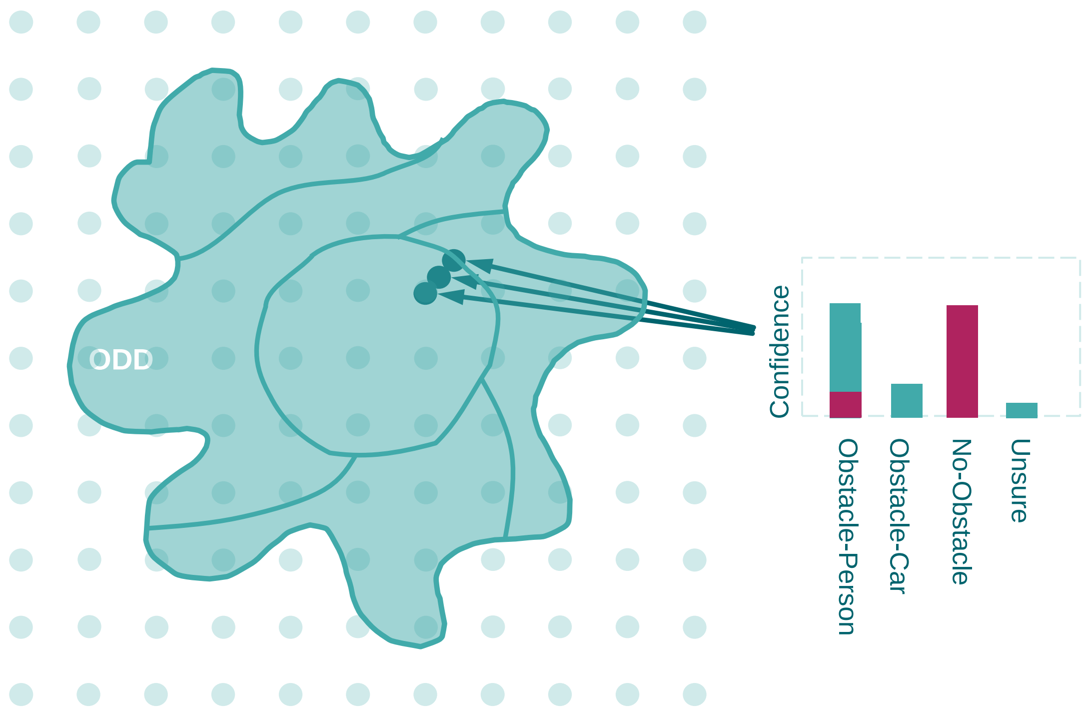
1 – Safe AI Principles & Tools



3 Robustness

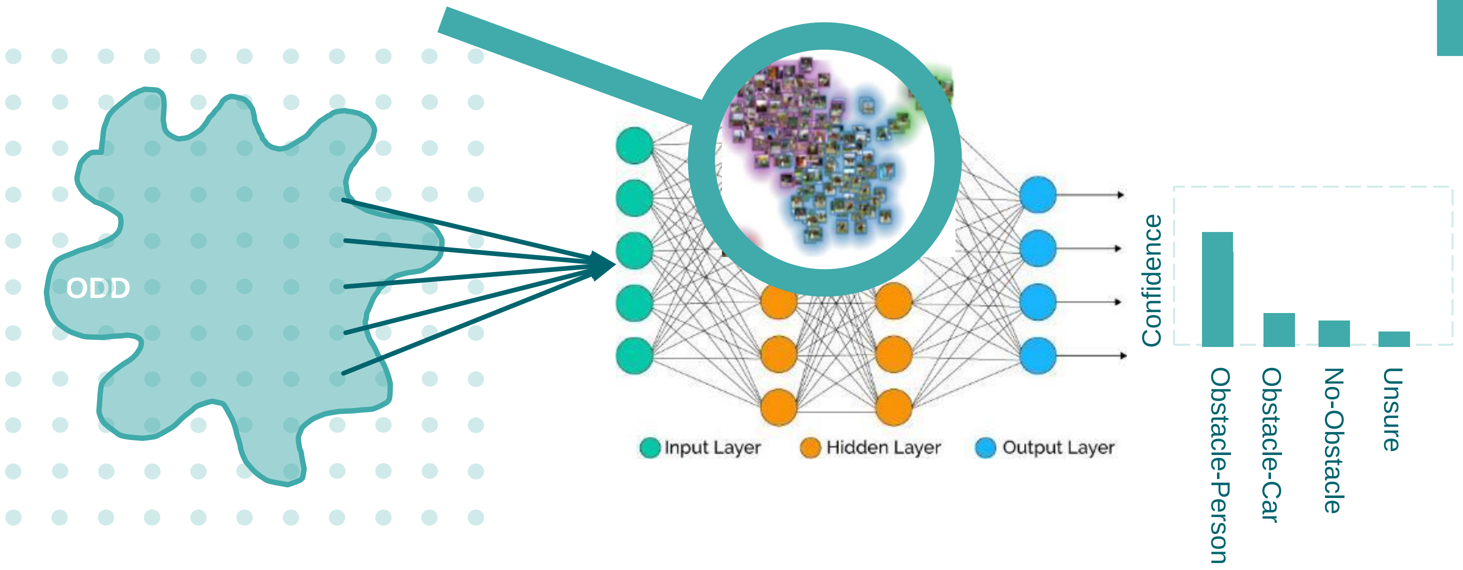
Why?

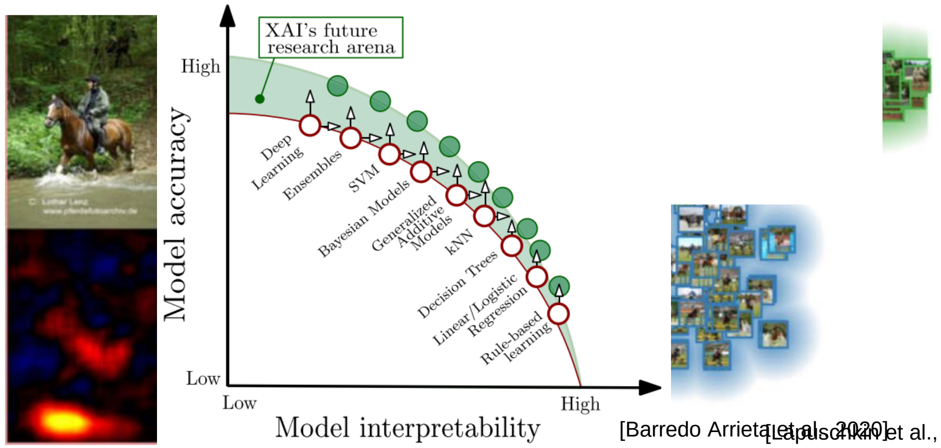
- Small perturbations in the input space shall generate small changes in the state space
- Perturbations may come from
  - Natural changes & noise
  - Adversarial attacks

What?

- Analysis through ML stress testing with perturbations & augmentations, edge case mining, …
- Mitigation through regularization

1 – Safe AI Principles & Tools





[Barredo Arrieta et al., 2020] [Lapuschkin et al., 2019]

4 Interpretability

Why?

- AI and ML models are often black boxes
- Interpreting behavior contributes to building trust

What?

- Different categories of interpretability approaches
  - Intrinsic vs. post-hoc
    - Intrinsic: ML models with simple structure
    - Post-hoc interpretation: Apply interpretation methods after model training
  - Model agnostic vs. Model specific
    - Model agnostic: work by analyzing input/output pairs
    - Model specific: open the black box; access to model internals
  - Local vs. global
    - Local: explains individual prediction (why did a model make a specific prediction?)
    - Global: explains entire model behavior

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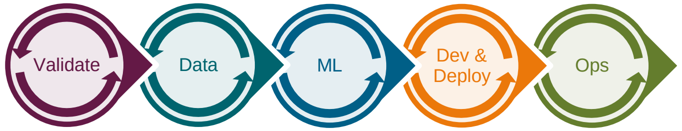
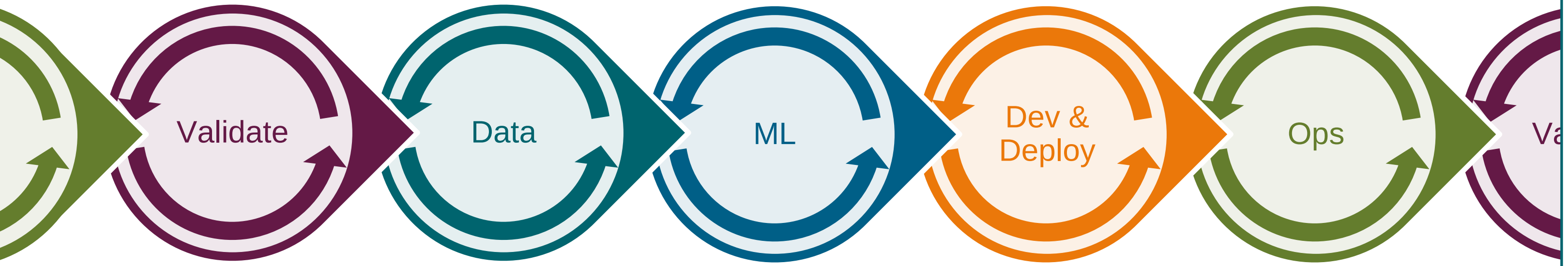


2 – Safe MLOps

Safe AI / MLOps Cycle for GoA4 Engineering



Validate

1. Monitor field operation
2. Mine & tag edge cases
3. Validate ML performance using SafeAI tools
4. Deliver validation report

Data

1. Curate new data batch
2. Build & refine data sets (Train/Val/Test)
3. Deliver data as new Train/Val/Test Sets

ML

1. Explore & revise ML options
2. Train, debug & optimize ML performance
3. Module test on test set
4. Deliver ML as ONNX model

Dev & Deploy

1. Optimize runtime, configure parameters & package ML model for Ops (ONNX, TensorRT tbd)
2. Create RTE node
3. Module test in simulation
4. Deliver Dev as ROS node

Ops

1. Integrate into system
2. Test system (SIL, SIM & HIL)
3. Release system to vehicle(s)
4. Operate in field
5. Deliver Ops as a running test vehicle with monitoring and logging functions

Why?

Safe AI based automation systems require an **AI / ML engineering process** that accounts for trust and safety with the goals:

- Provide to the engineers the right tools and infrastructure that supports agile and frequent iterations in ML development and validation (on top of DevOps)
- Enable thorough validation of developed AI / ML, also at the edge of the ODD
- Allow for systematic sampling of the ODD (addressing **quantity** & **quality**)
- Auditable: traceable, reproduceable, measurable
- Highly automated → less error prone & less costly

What?

- Implement an agile AI / MLOps cycle addressing ML optimization, deployment, operation, validation, and data feedback → automated wherever possible
- Develop an infrastructure that persists and serves data and artifacts of the AI / MLOps cycle and that takes the admin burden from the ML experts
- Develop and integrate a runtime monitoring for situation novelty and uncertainty assessment and logging in the automation RTE

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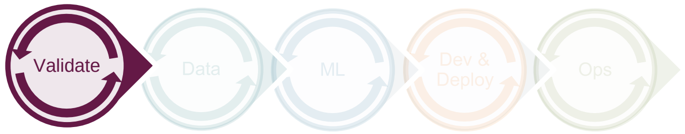
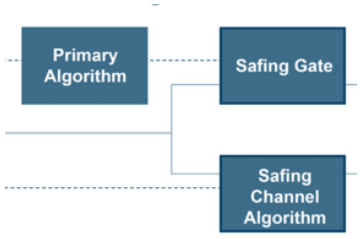
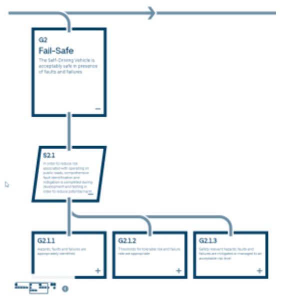


3 – Safe AI System

1 Safety Architecture

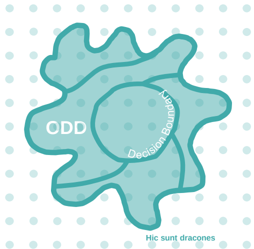


3 Safety Case



5 Interdisciplinarity/ Community

2 ODD description



4 Safety Metrics / Performance Indicators

6 Norms & Regulation

IEC ISO CENELEC

Why?

GoA4 operation with AI / ML inside requires safety in the design, including

- A system safety architecture
- Support from current and future norms and regulation for a commercial rollout
- A homologation strategy

What?

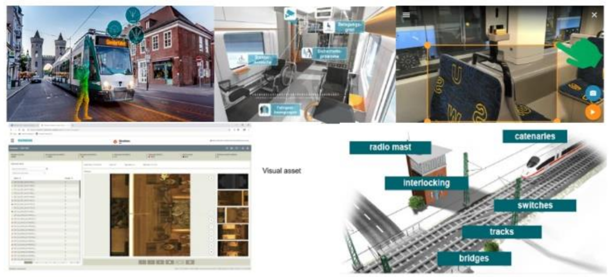
- Analysis and comparison of suitable safety architectures (considering several candidates, e.g., Doer-Checker, Simplex, runtime monitoring, Failover, 2-of-2, Fused outputs …); choice of best candidate
- Description of a GoA4 operational design domain (ODD)
- Creation of a safety case for GoA4 operation with AI / ML inside
- Definition of safety metrics and validation procedures
- Continuous dialogues in the AI, Safety, Rail and other verticals industry community
- Contributions to activities for AI regulation & standardization for the example of GoA4

Safety Case = A structured written argument, supported by evidence, justifying that a system is acceptably safe for intended use.

Conclusion
AI in Rail

1. OPPORTUNITIES

Artificial Intelligence is a key and differentiator in several opportunities in Rail.

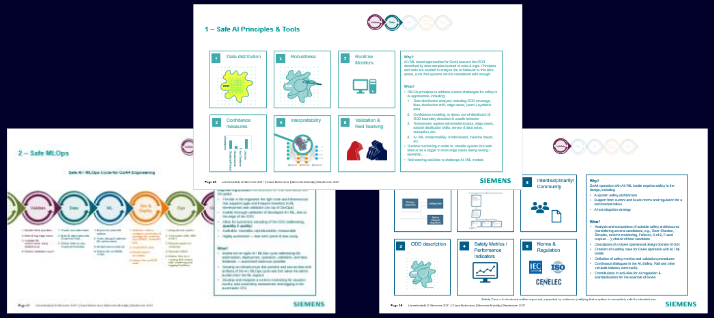


2. MATURE
Products available

- Products and services in use for non-safety critical functions, internal processes, digital assistants, human-in-the-loop, …
- Enterprise grade AI ecosystem enables efficient development

3. CHALLENGES
Needs R&D

- Safe AI for full automation in safety-critical applications
- Safe AI is challenging, but opens new business opportunities esp. in automation
- Safe AI is active R&D field across industries



Thanks to the many colleagues contributing ☺

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Thank you for your Interest

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