Ergo, SMIRK is Safe: A Safety Case for a Machine Learning Component in a Pedestrian Emergency Brake System

Markus Borg markus.borg@codescene.com

10th Scandinavian Conference on System & Software Safety, Nov 22, 2022





Open ML safety case

arxiv:2204.07874

Computer Science > Software Engineering

[Submitted on 16 Apr 2022 (v1), last revised 15 Sep 2022 (this version, v2)]

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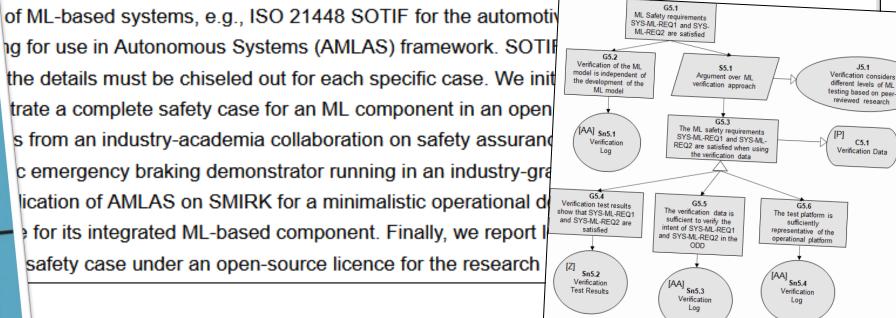
Markus Borg, Jens Henriksson, Kasper Socha, Olof Lennartsson, Elias Sonnsjö Lönegren, Thanh Bui, Piotr Tomaszewski, Sankar Raman Sathyamoorthy, Sebastian Brink, Mahshid Helali Moghadam

Integration of Machine Learning (ML) components in critical applications introduces novel challenges for software certification and verification. New safety standards and technical guidelines are under development to

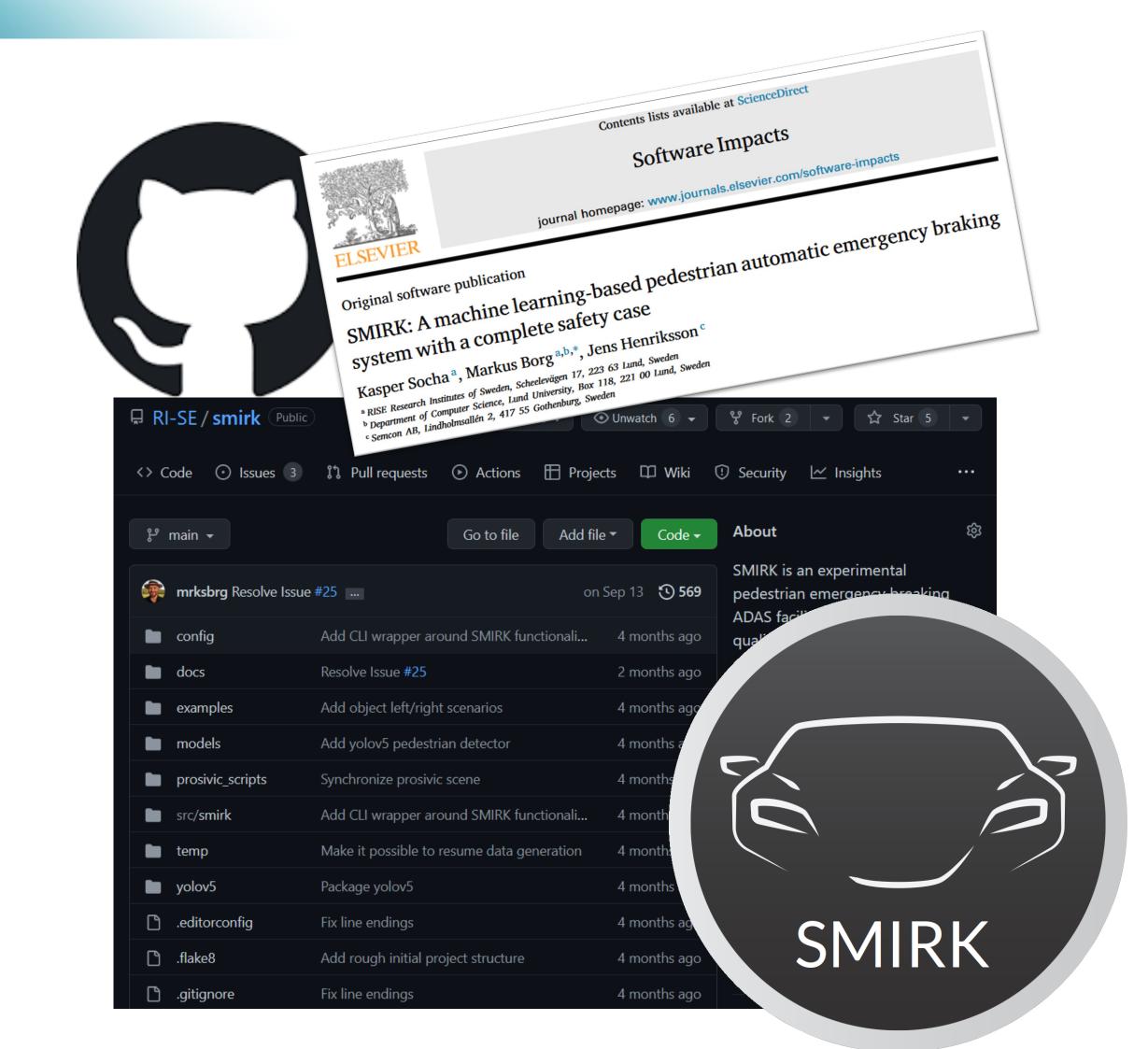
Software Quality Journal

Editor-in-Chief Rachel Harrison

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Open ML-based demonstrator







Introduction

Who is Markus?

Development engineer, ABB	20
 Process automation 	
PhD student, Lund University	20
 Traceability, change impact analysis 	
Senior researcher, RISE	20
 Al engineering and functional safety 	
Principal researcher, CodeScene	20
 Software engineering intelligence 	





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15-2022

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Research Institutes of Sweden





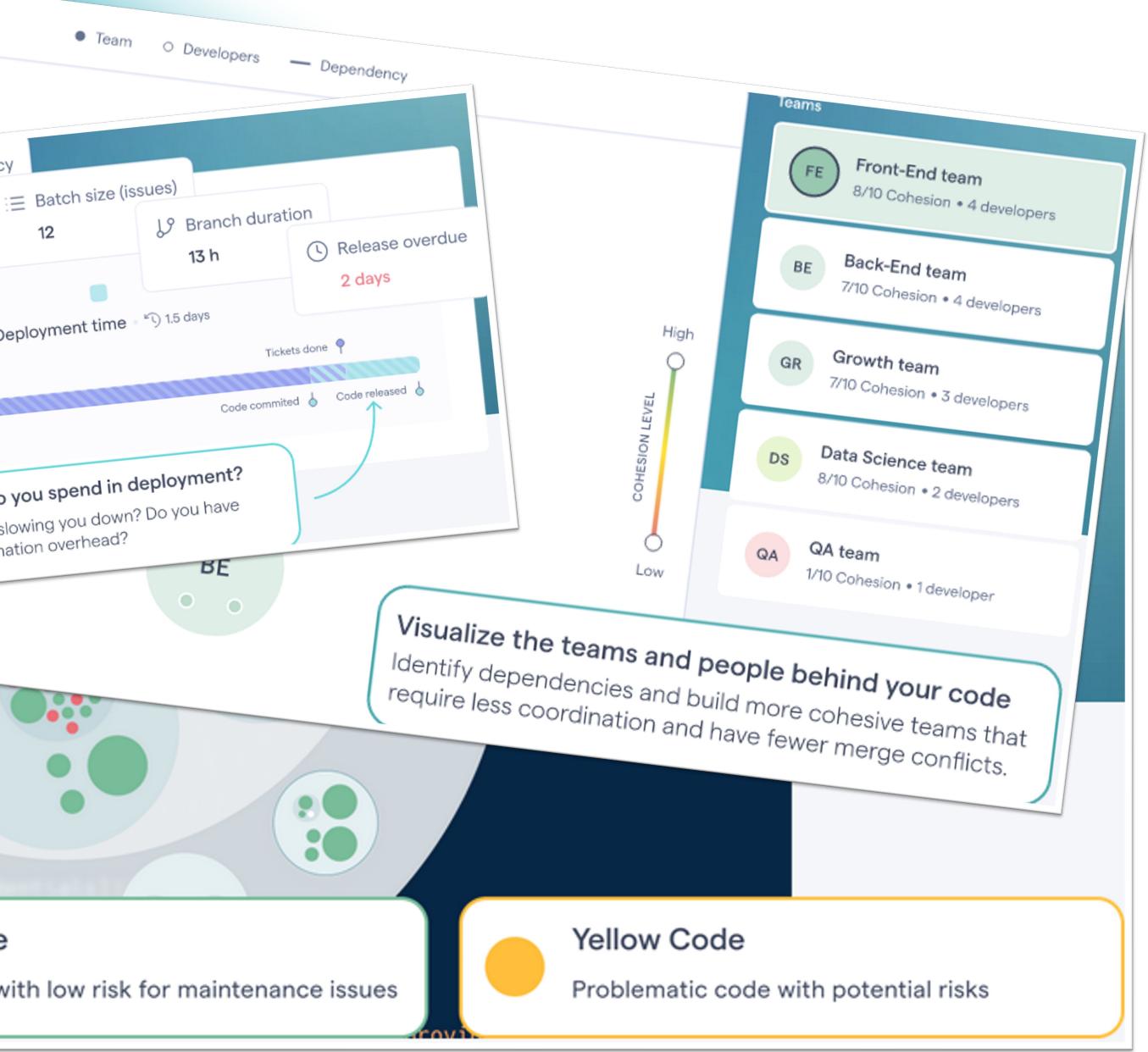




CodeScene

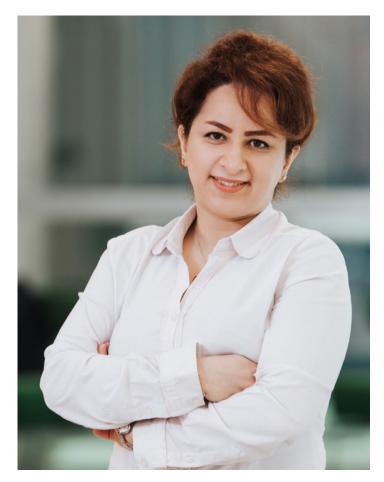
	-√- Release frequency every 12 h
Yearly average Development time	う 7 days
Knowing what affects we time to market and the Where you See https event-withe	A can type a can type clojure.ja clojure.str cognitect.aws cognitect.aws.
Red Code Unhealthy code with high mainter	nance risks

codescene.com





Markus Borg



Mashid Helali





Kasper Socha



Thanh Bui



Piotr Tomaszewski







Sencon



Olof Lennartsson

INFOTIV



Elias Sonnsjö Lönegren



Sankar Sathyamoorthy

CCMBITECH



Sebastian Brink









Standards and guidelines are high-level...

... must get our hands dirty with ML details

Lack of: - experience reports - open demonstrator systems

"How to demonstrate and share a complete ML

safety case for an open ADAS?"



Two teasers! Development of

SMIRK Safety case



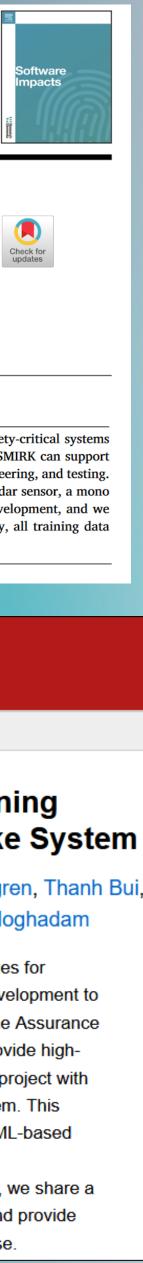
Contents lists available at ScienceDirect

Software Impacts

journal homepage: www.journals.elsevier.com/software-impacts

Original software publication

SMIRK: A machine learning-based pedestrian automatic emergency braking system with a complete safety case



Kasper Socha^a, Markus Borg^{a,b,*}, Jens Henriksson^c

^a RISE Research Institutes of Sweden, Scheelevägen 17, 223 63 Lund, Sweden

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ARTICLE INFO

Keywords: Automotive demonstrator Advanced driver-assistance system Pedestrian automatic emergency braking Machine learning Computer vision Safety case

ABSTRACT

SMIRK is a pedestrian automatic emergency braking system that facilitates research on safety-critical systems embedding machine learning components. As a fully transparent driver-assistance system, SMIRK can support future research on trustworthy AI systems, e.g., verification & validation, requirements engineering, and testing. SMIRK is implemented for the simulator ESI Pro-SiVIC with core components including a radar sensor, a mono camera, a YOLOv5 model, and an anomaly detector. ISO/PAS 21448 SOTIF guided the development, and we present a complete safety case for a restricted ODD using the AMLAS methodology. Finally, all training data used to train the perception system is publicly available.

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Computer Science > Software Engineering

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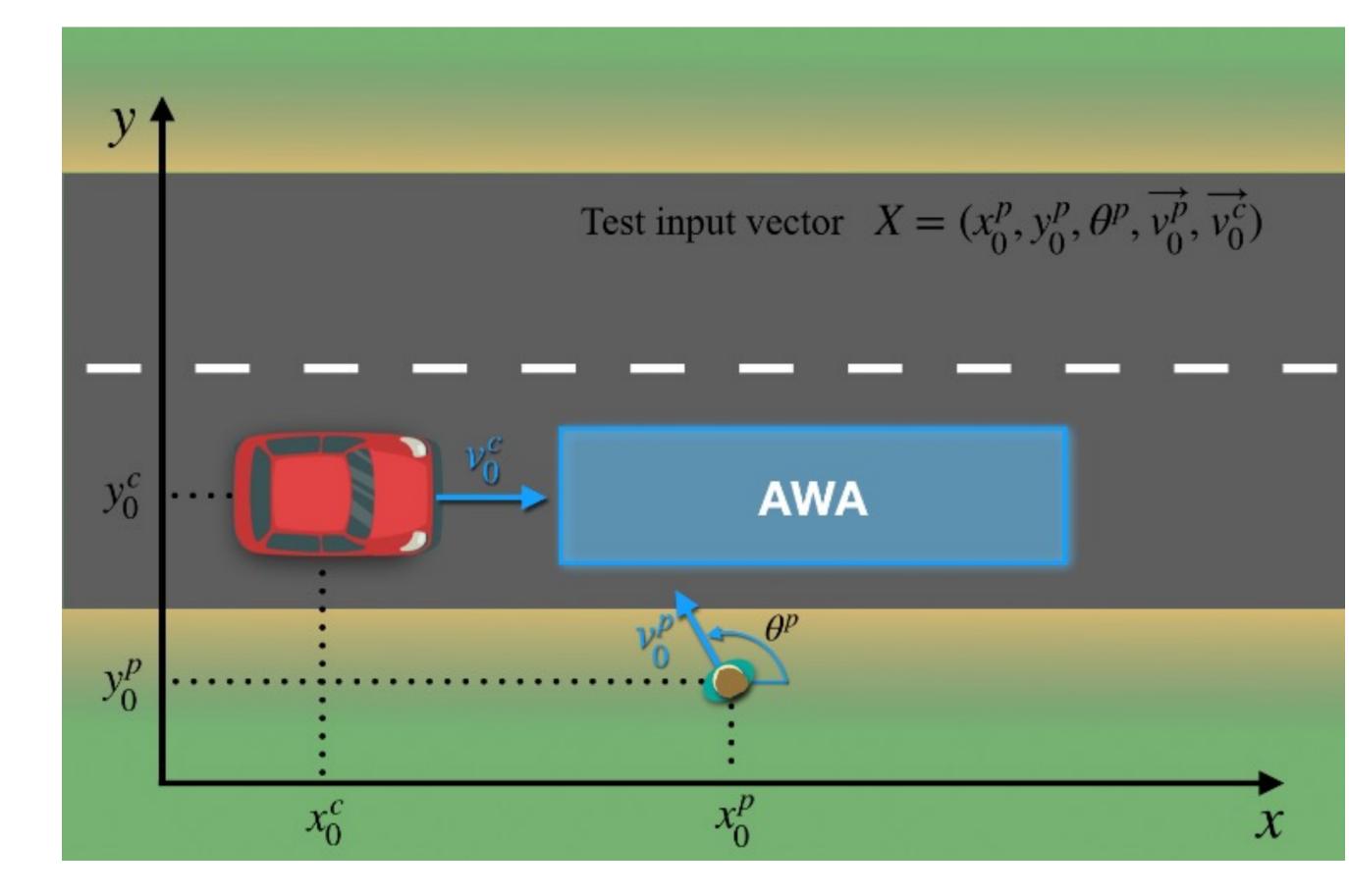
Integration of Machine Learning (ML) components in critical applications introduces novel challenges for software certification and verification. New safety standards and technical guidelines are under development to support the safety of ML-based systems, e.g., ISO 21448 SOTIF for the automotive domain and the Assurance of Machine Learning for use in Autonomous Systems (AMLAS) framework. SOTIF and AMLAS provide high-level guidance but the details must be chiseled out for each specific case. We initiated a research project with the goal to demonstrate a complete safety case for an ML component in an open automotive system. This paper reports results from an industry-academia collaboration on safety assurance of SMIRK, an ML-based pedestrian automatic emergency braking demonstrator running in an industry-grade simulator. We demonstrate an application of AMLAS on SMIRK for a minimalistic operational design domain, i.e., we share a complete safety case for its integrated ML-based component. Finally, we report lessons learned and provide both SMIRK and the safety case under an open-source licence for the research community to reuse.



Development of SMIRK



Reverse engineering from PeVi





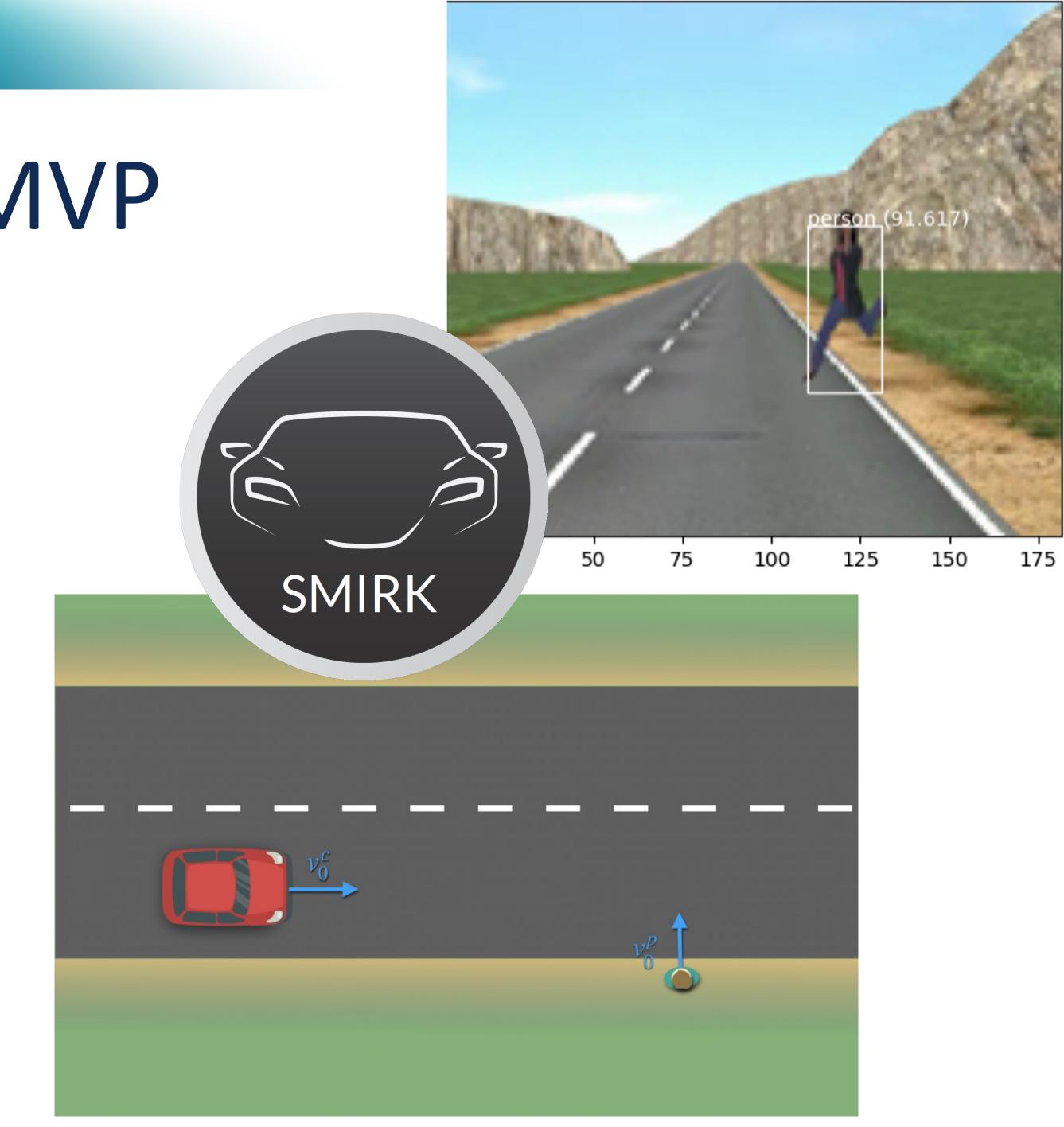




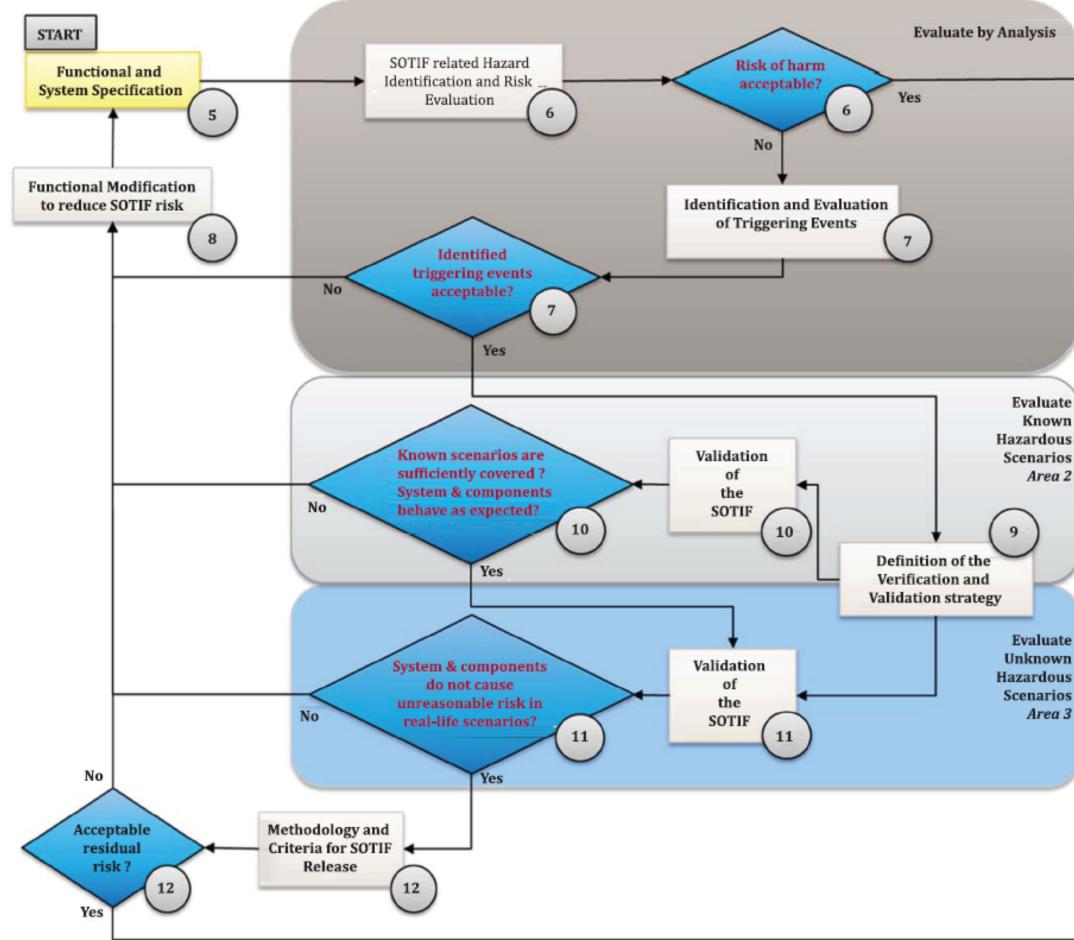
Open Source ADAS MVP

- In ESI Pro-SiVIC
- Pedestrian emergency braking
- Mono-camera and radar
- ML-based pedestrian recognition





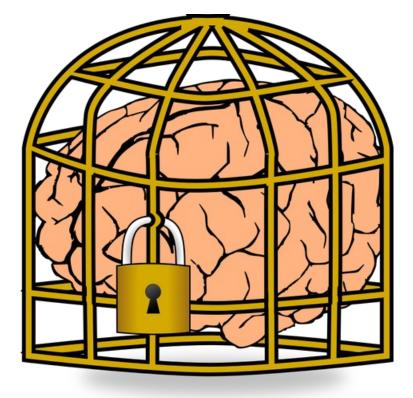
Follow the process in ISO 21448 SOTIF



Review END Risk accepted Evaluate Known Scenarios Area 2 Evaluate Unknown Scenarios Area 3

Primary hazard to tackle: False postives





Safety cage: an app machine learning s

Sankar Raman Sathyamod





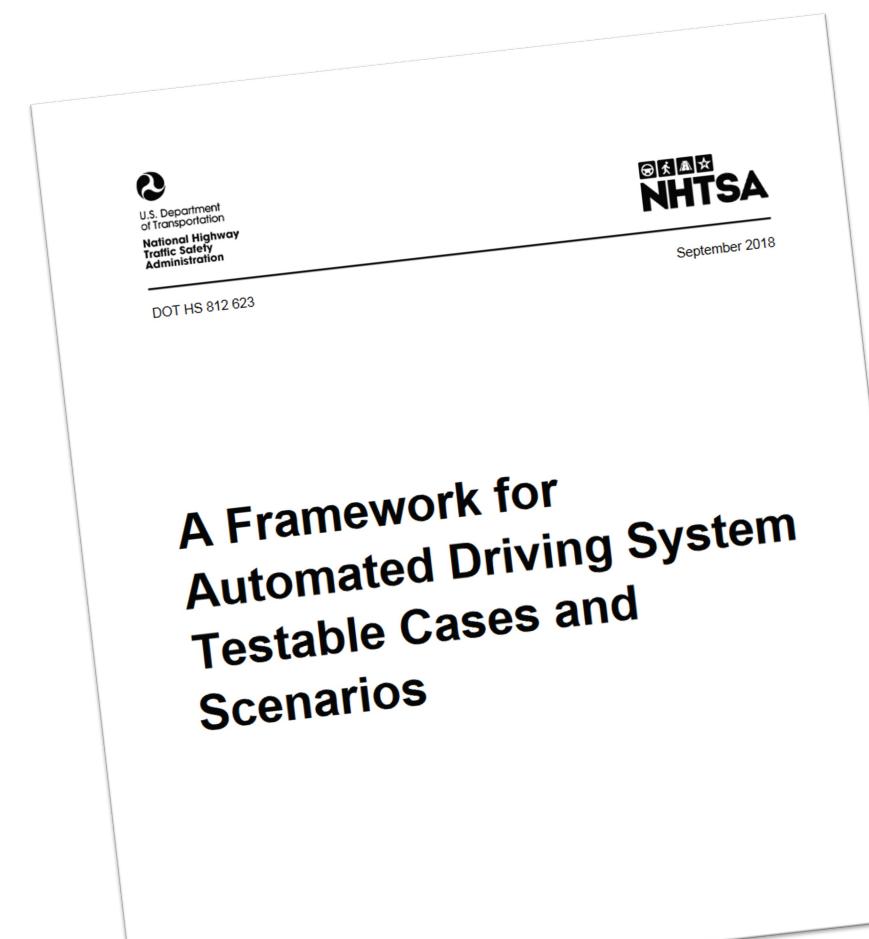




MDDON Compony

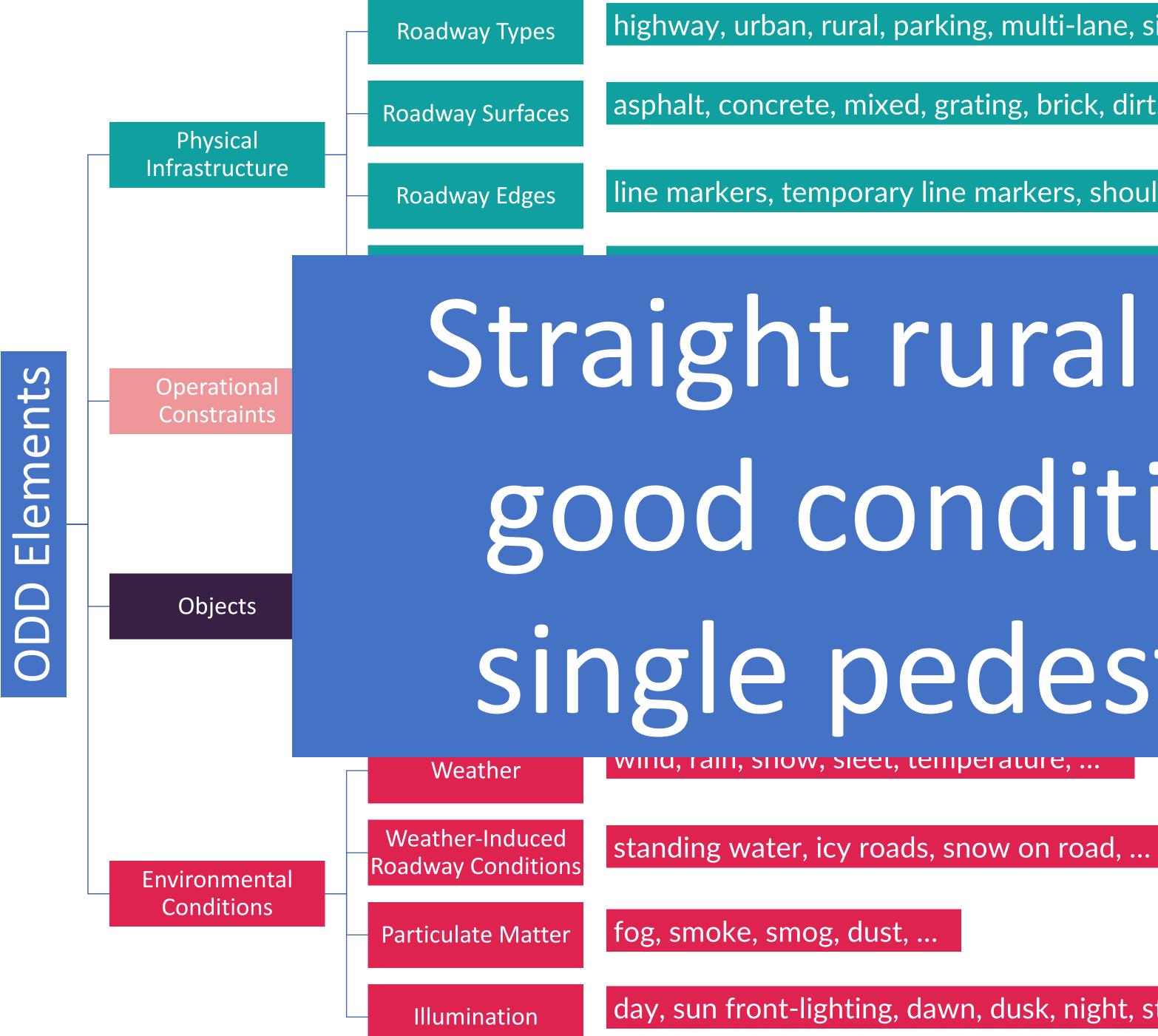


MVP Operational Design Domain



Thorn E, Kimmel SC, Chaka M, et al (2018)

Tech. rep., US Department of Transportation National Highway Traffic Safety Administration



highway, urban, rural, parking, multi-lane, single lane, on/off ramps, intersections, roundabouts, ...

asphalt, concrete, mixed, grating, brick, dirt, gravel, ...

line markers, temporary line markers, shoulder, concrete barriers, rails, cones, ...

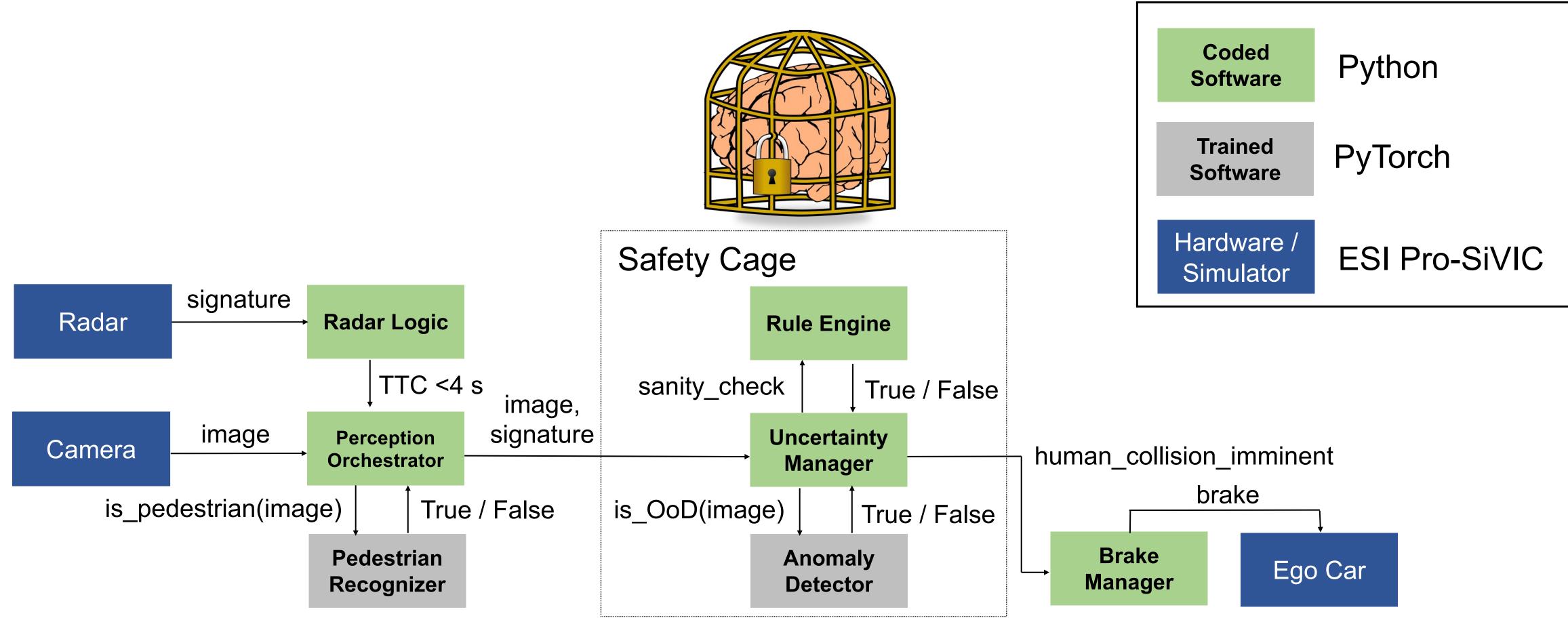
Straight rural road, good conditions, single pedestrian

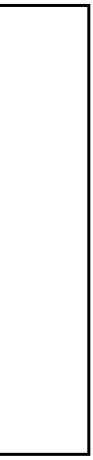
day, sun front-lighting, dawn, dusk, night, street lights, headlights, oncoming vehicle lights, ...





Logical View of the SMIRK Architecture





Requirements engineering...

System requirements

3.3 Machine Learning Safety Requirements [H]

This section refines SYS-SAF-REQ into two separate requirements corresponding to false positives and false negatives, respectively.

- SYS-ML-REQ1: The pedestrian recognition component shall detect pedestrians if the radar tracking component returns TTC < 4s for the corresponding object.
- SYS-ML-REQ2: The pedestrian recognition component shall reject input that does not resemble the training data.

3.3.1 Performance Requirements

This section specifies performance requirements corresponding to the ML safety requirements with a focus on quantitative targets for the pedestrian recognition component. All requirements below are restricted to pedestrians on or close to the road.

- SYS-PER-REQ1: The pedestrian recognition component shall identify pedestrians with an accuracy of 0.93 when they are within 50 meters.
- SYS-PER-REQ2: The false negative rate of the pedestrian recognition component shall not exceed 7% for pedestrians when they are detected by the radar tracking component within 50 meters.
- SYS-PER-REQ3: The false positive rate of the pedestrian recognition component shall not exceed 0.01% for objects detected by the radar tracking component with a TTC < 4s
- SYS-PER-REQ4: In a sequence of images from a video feed any pedestrian to be detected shall not be missed in more than 1 out of 5 frames.
- SYS-PER-REQ5: The pedestrian recognition component shall determine the position of pedestrians within 50 cm of their actual position.
- SYS-PER-REQ6: The pedestrian recognition component shall allow an inference speed of at least 10 FPS on the target platform.





Data requirements

2.1 Relevant

This desideratum considers the intersection between the dataset and the supported dynamic driving task in the ODD. The SMIRK training data will not cover operational environments that are outside of the ODD, e.g., images collected in heavy snowfall.

- DAT-REL-REQ1: All data samples shall represent images of a road from the perspective of a vehicle.
- DAT-REL-REQ2: The format of each data sample shall be representative of that which is captured using sensors deployed on the ego vehicle.
- DAT-REL-REQ3: Each data sample shall assume sensor positioning representative of the positioning used on the ego vehicle.
- DAT-REL-REQ4: All data samples shall represent images of a road that corresponds to the ODD.
- DAT-REL-REQ5: All data samples containing pedestrians shall include one single pedestrian.
- DAT-REL-REQ6: Pedestrians included in data samples shall be of a type that may appear in the ODD.
- DAT-REL-REQ7: All data samples representing non-pedestrian OOD objects shall be of a type that may appear in the ODD.





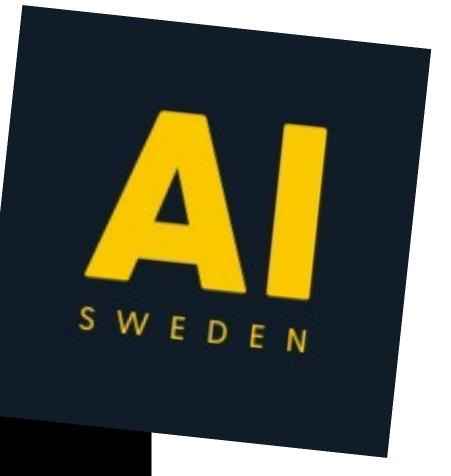
Generate Training Data in ESI Pro-SiVIC

Synthetic data that cover the Operational Design Domain



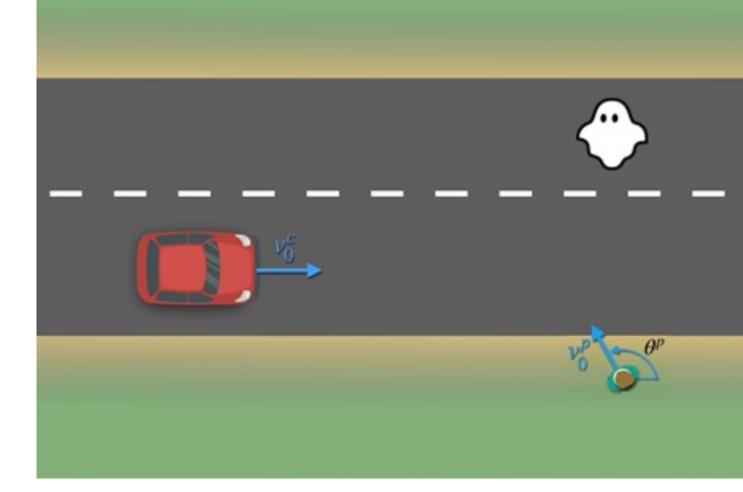
https://github.com/RI-SE/smirk/tree/main/pedestrian-generator

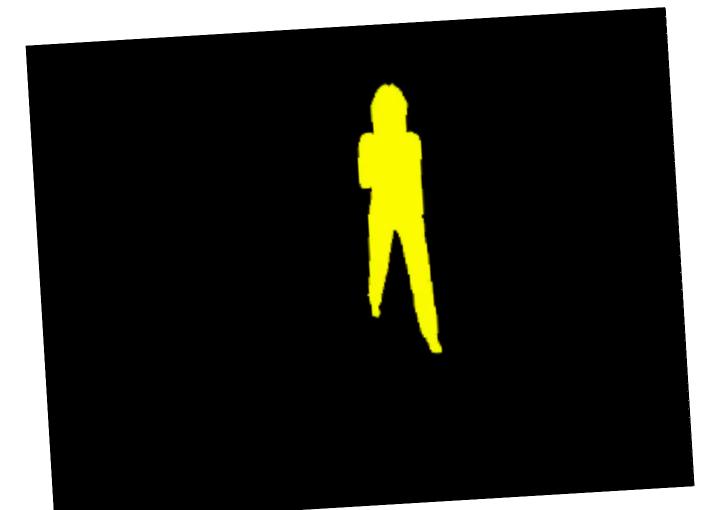
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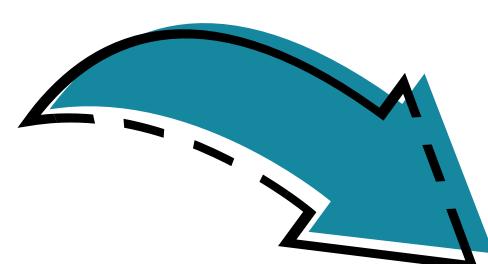


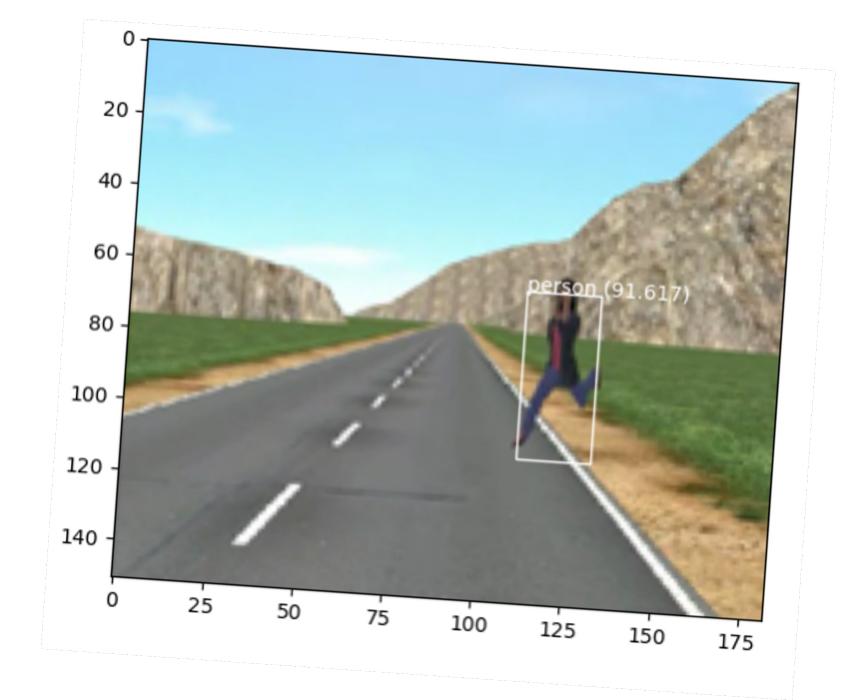


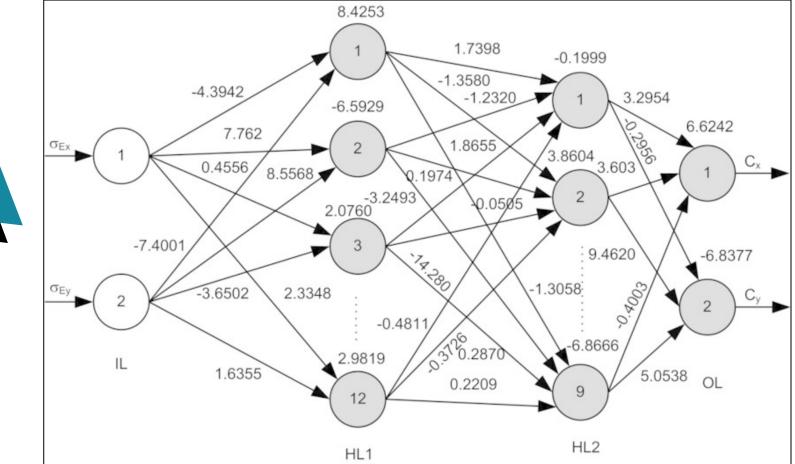
The SMIRK MVP









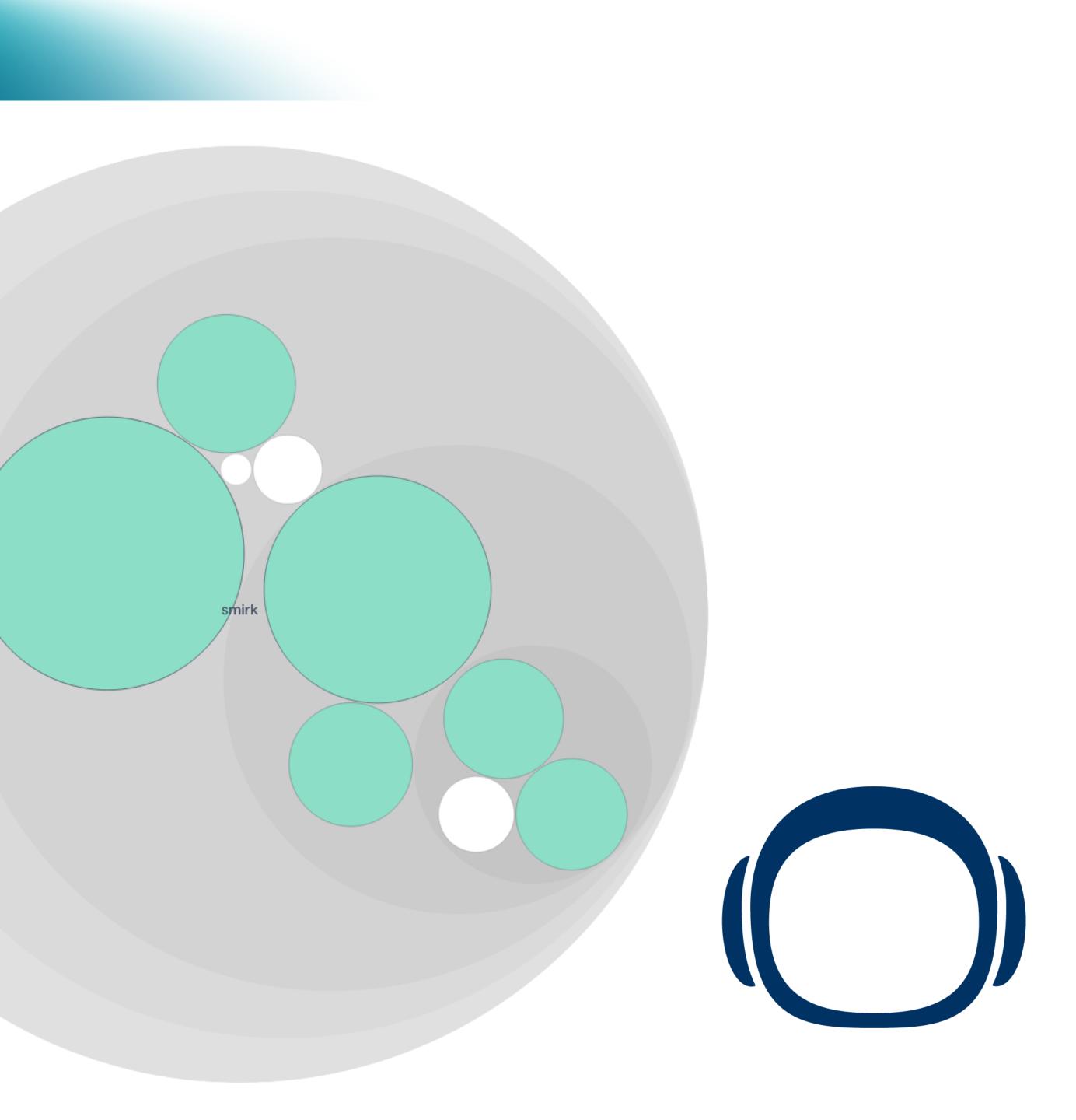


SMIRK CodeScene Analysis

11 files

Good code health







Safety Case Development Using AMLAS



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Assuring Autonomy International Programme

Assuring Autonomy Internationa

Addressing global challenges in assuring the safety of robotics and

Goal Structuring Notation Community Standard Version 2

> The Assurance Case Working Group (ACWG)

> > SCSC-1418







Guidance on the Assurance of Machine Learning in Autonomous Systems (AMLAS)

Richard Hawkins, Colin Paterson, Chiara Picardi, Yan Jia, Radu Calinescu and Ibrahim Habli.

Assuring Autonomy International Programme (AAIP) University of York

Version 1.1, March 2021

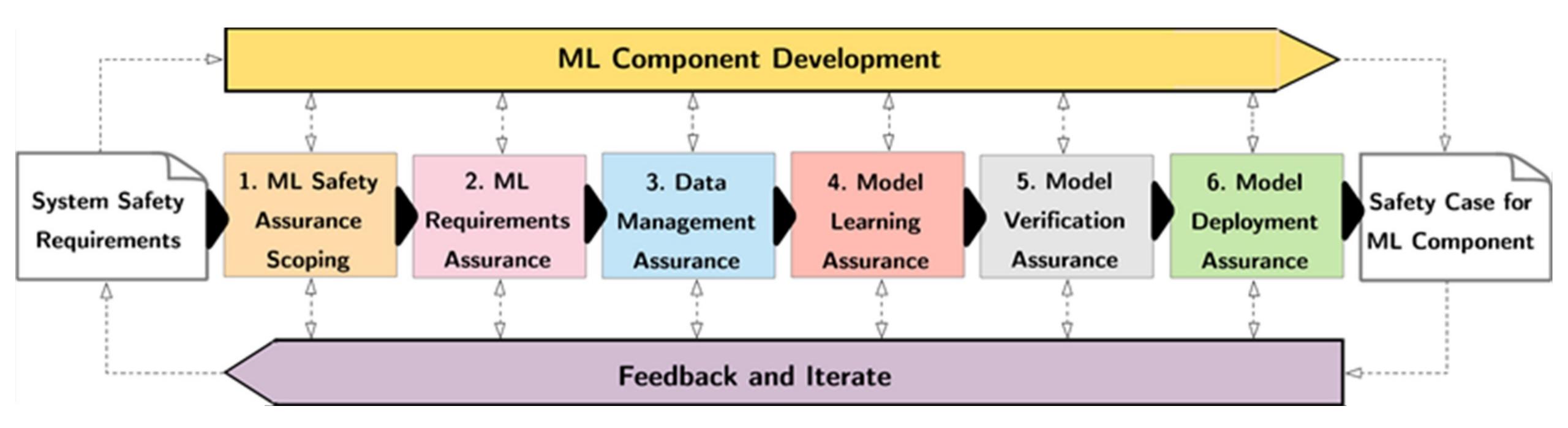
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Contact : firstname.lastname@york.ac.uk.



Follow the AMLAS process

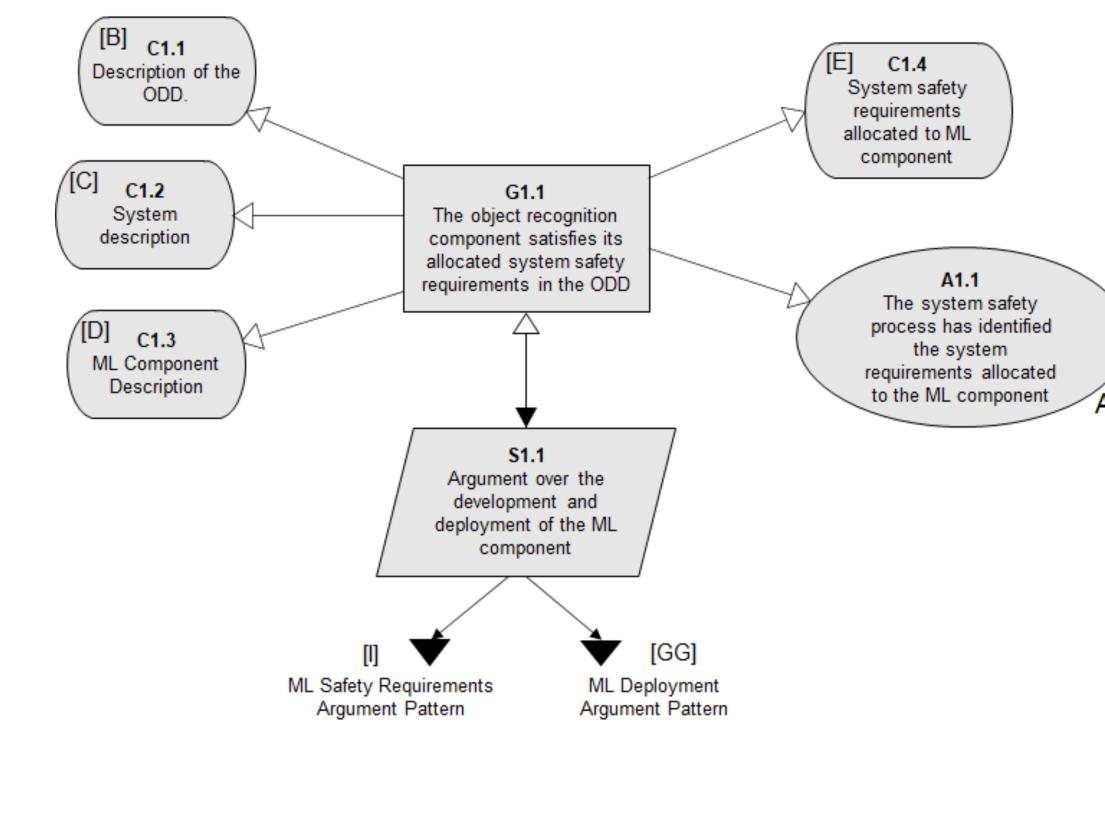


1. Safety Assurance Scoping

ID	Title	Input to	Output from	Where?	Status
[A]	System Safety Requirements	1, 6		SRS Sec 3.1	Done
[B]	Description of Operating Environment of System	1, 6		SRS Sec 4	Done
[C]	System Description	1, 6		SRS Sec 2	Done
[D]	ML Component Description	1		MLCS Sec 2	(J) Outlier detection missing
[E]	Safety Requirements Allocated to ML Component	2	1	SRS Sec 3.2	Done
[F]	ML Assurance Scoping Argument Pattern	1		SRS Sec 6	Done
[G]	ML Safety Assurance Scoping Argument		1	SRS Sec 7	Done
[H]	ML Safety Requirements	3, 4, 5	2	SRS Sec 3.3	Done
[1]	ML Safety Requirements Argument Pattern	2		SRS Sec 8	Done
[1]	ML Safety Requirements Validation Results		2	SRS Sec 9	Done
[K]	ML Safety Requirements Argument		2	SRS Sec 10	Done
[L]	Data Requirements		3	DMS Sec 2	Done
[M]	Data Requirements Justification Report		3	DMS Sec 3	Done
[N]	Development Data		3	TBD	(M) Hosting needed
[O]	Internal Test Data		3	TBD	(M) Hosting needed
[P]	Verification Data		3	TBD	(M) Hosting needed
[Q]	Data Generation Log		3	DMS Sec 4	Links to code needed
[R]	ML Data Argument Pattern	3		DMS Sec 5	Done
[S]	ML Data Validation Results		3	DMS Sec 6	(K) Validation scripts needed
[T]	ML Data Argument		3	DMS Sec 7	Done
[U]	Model Development Log		4	MLCS Sec 3	(K) Add links to code
[V]	ML Model	5, 6	4	TBD	(K) Need to upload model
[W]	ML Learning Argument Pattern	4		MLCS Sec 5	Done
[X]	Internal Test Results		4	Protocols	(K) Create test report
[Y]	ML Learning Argument		4	MLCS Sec 6	Done
[Z]	ML Verification Results		5	Protocols	(J) Measure slices
[AA]	Verification Log		5	STS Sec 3	(M) Need to describe metrics
[BB]	ML Verification Argument Pattern	5		STS Sec 5	Done
[CC]	ML Verification Argument		5	STS Sec 6	Done
[DD]	Erroneous Behaviour Log		6	DS Sec 4	(M) Need to report lessons
[EE]	Operational scenarios	6		STS Sec 4.1	Done
[FF]	Integration Testing Results		6	Protocols	(K?) Not started
[GG]	ML Deployment Argument Pattern	6		DS Sec 5	Done
[HH]	ML Deployment Argument		6	DS Sec 6	Done



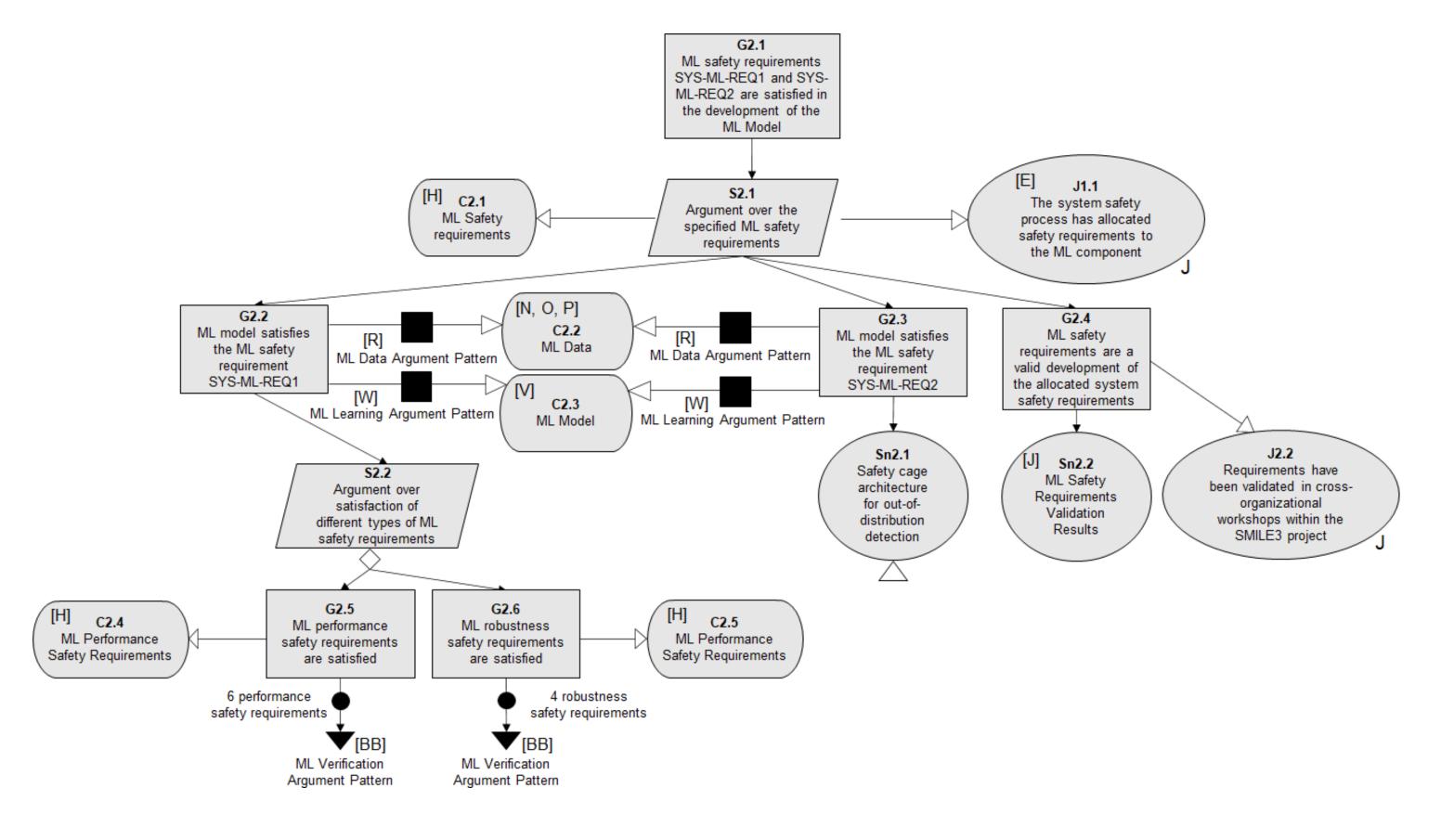
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github.com/RI-SE/smirk



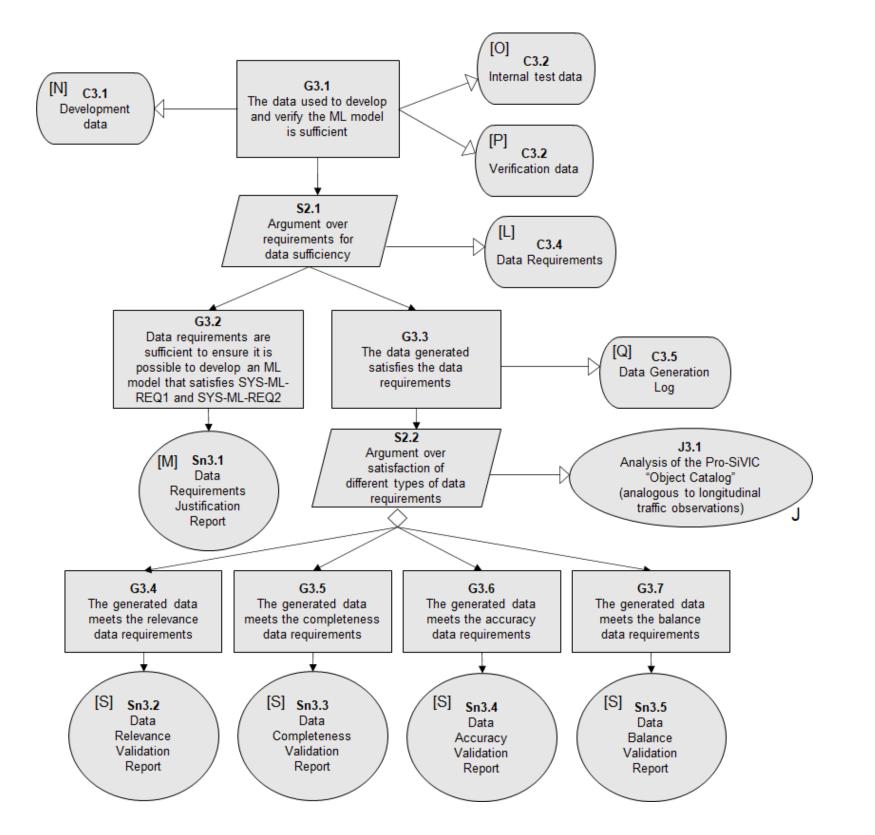
2. Requirements Assurance



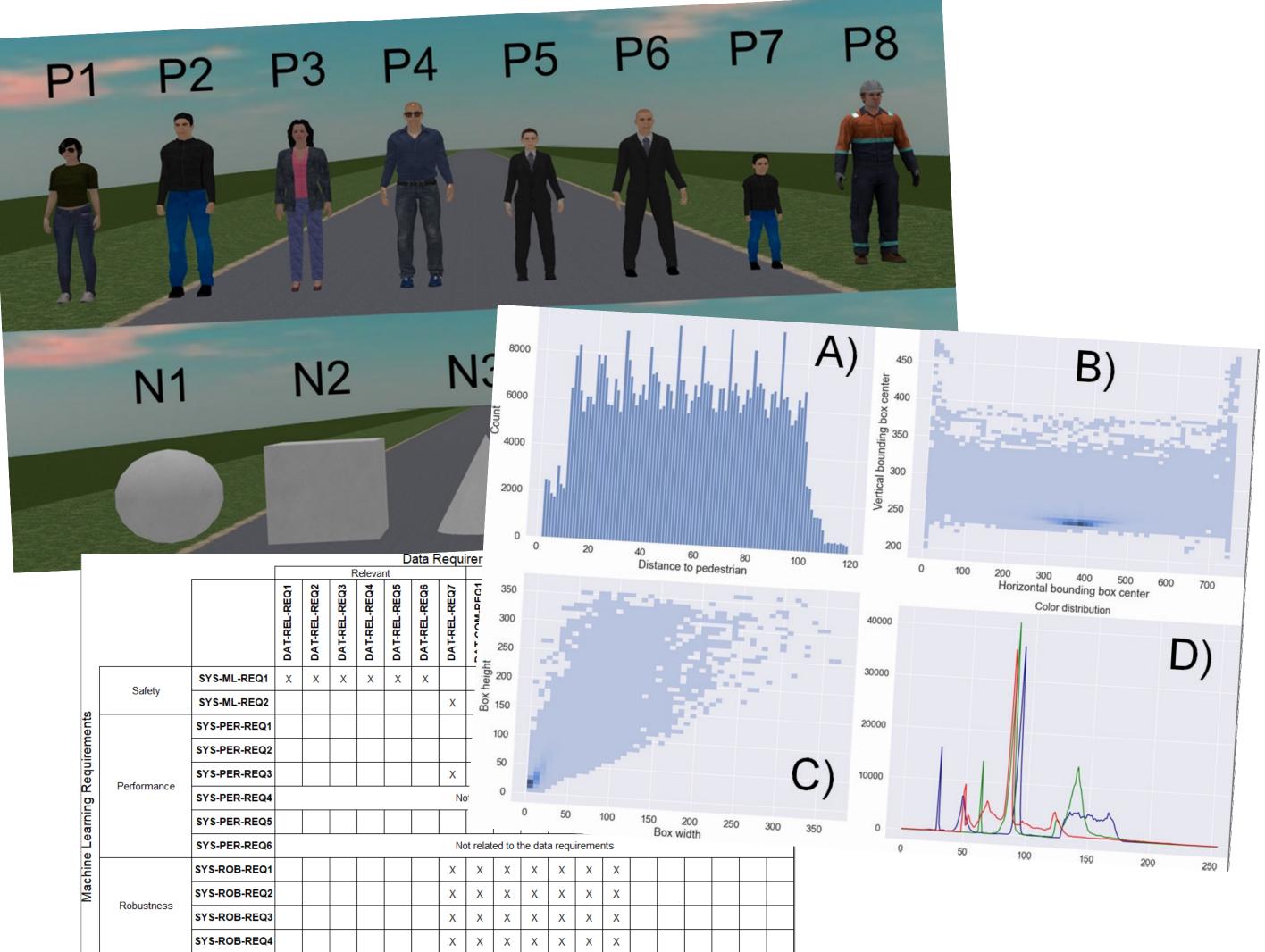
codescene.com

Formal inspections

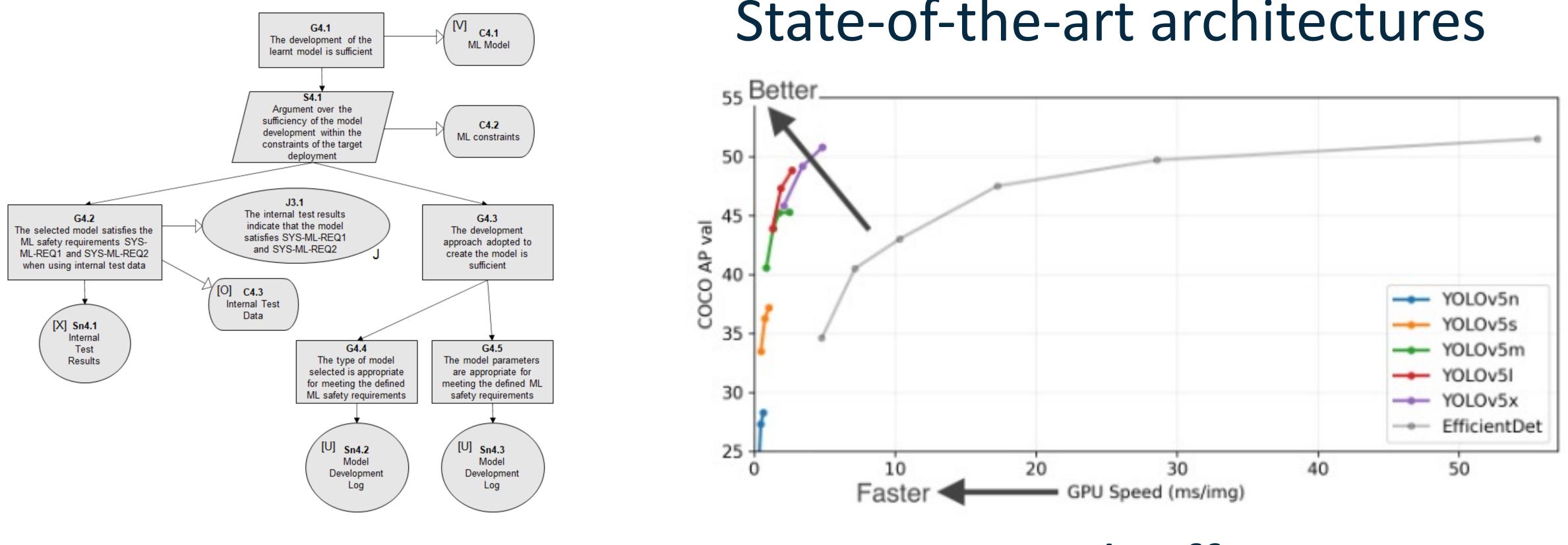
3. Data Management Assurance



1) Relevance 2) Completeness 3) Accuracy 4) Balance



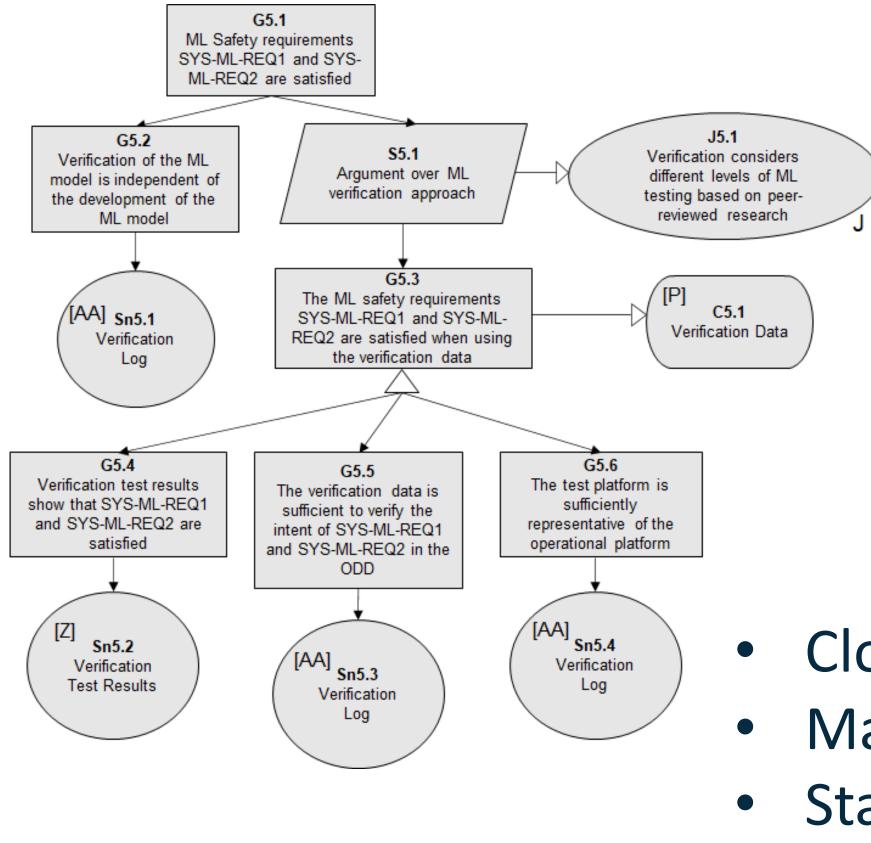
4. Model Learning Assurance



State-of-the-art architectures

Tradeoffs

5. Model Verification Assurance

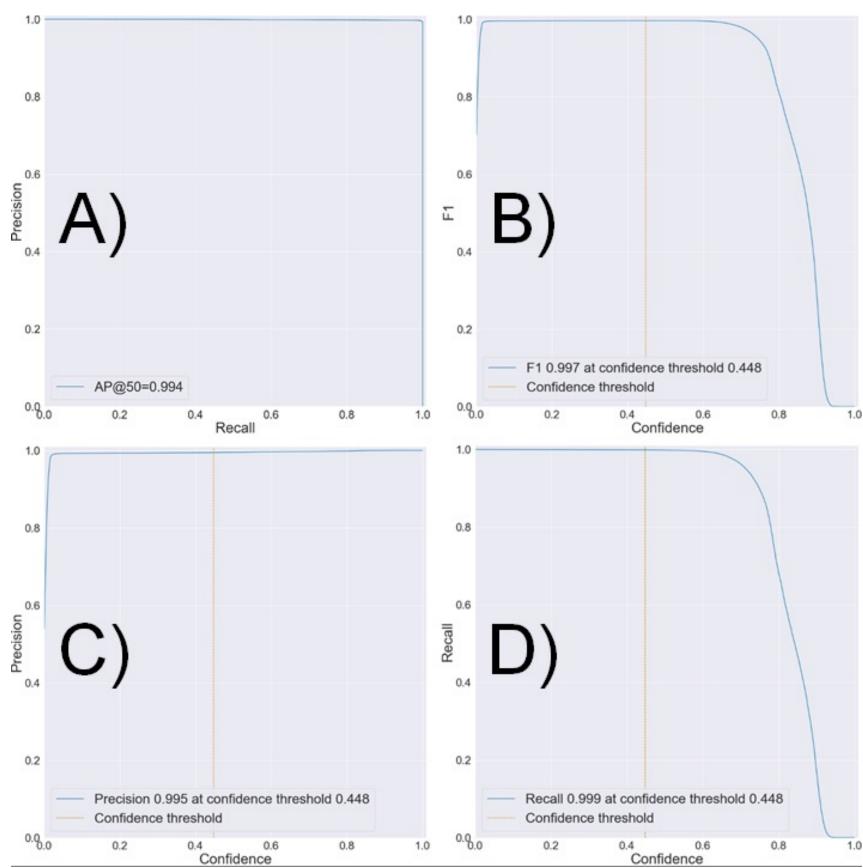


Analysis of subsets

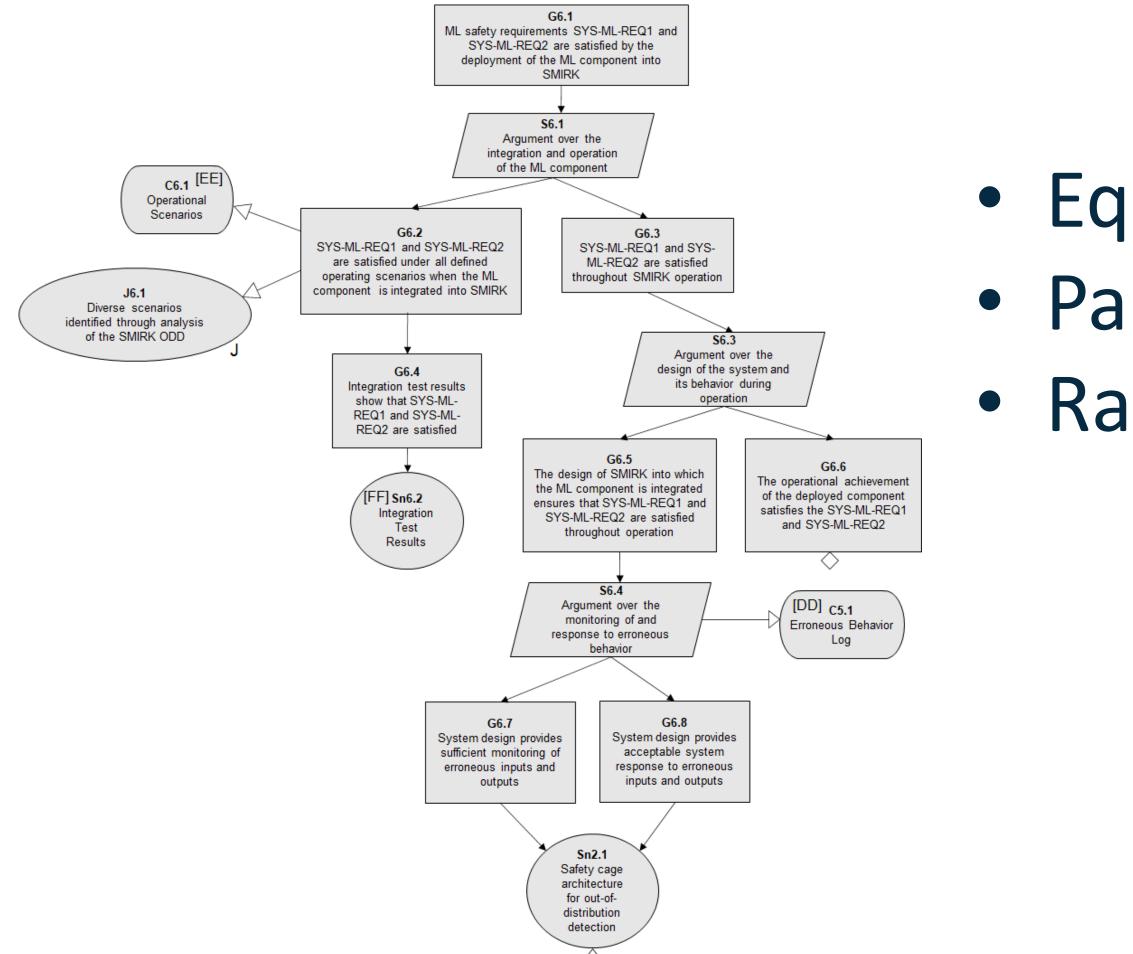
- Close/Far away
- Male/Female/Children
- Standing/Walking/Running

. . .

ay e/Children lking/Running

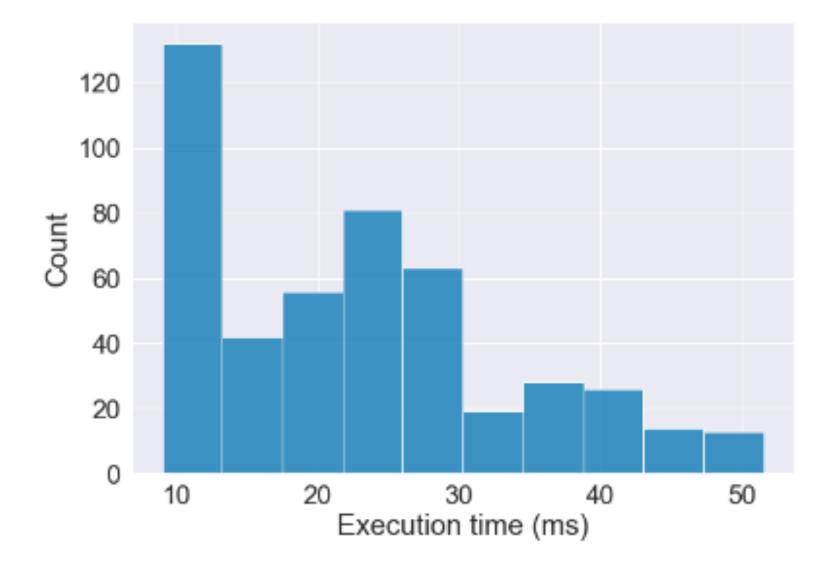


6. Model Deployment Assurance



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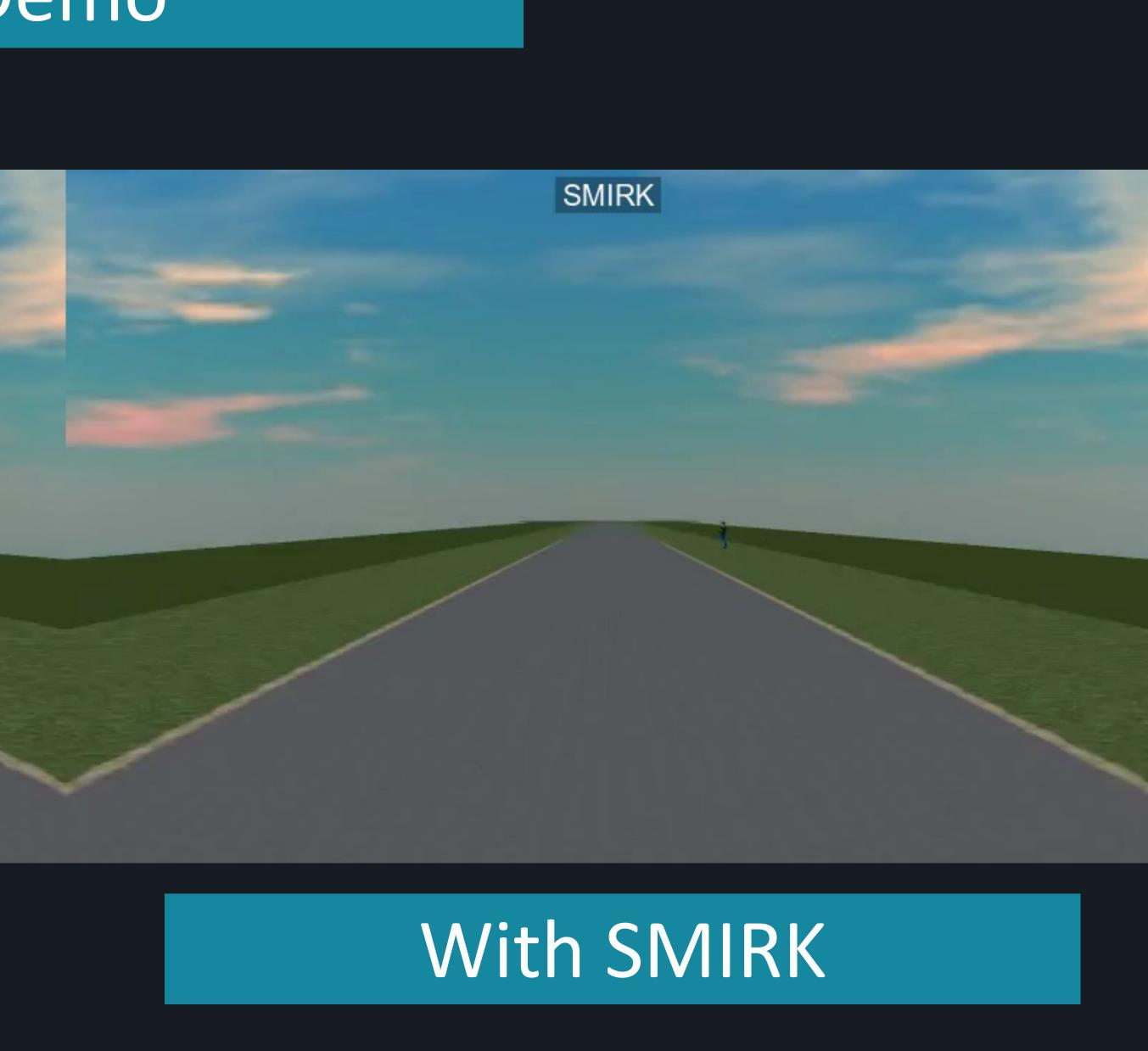
Integration testing
Equivalence partioning
Pairwise testing
Random testing





Without braking

Demo





Lessons Learned and Wrap-up



Lessons Learned

SOTIF and AMLAS compatible

codescene.com

- Simulated data threatens validity
 - of negative samples

Evaluation of object detection models is hard

Open ML safety case

arxiv:2204.07874

Computer Science > Software Engineering

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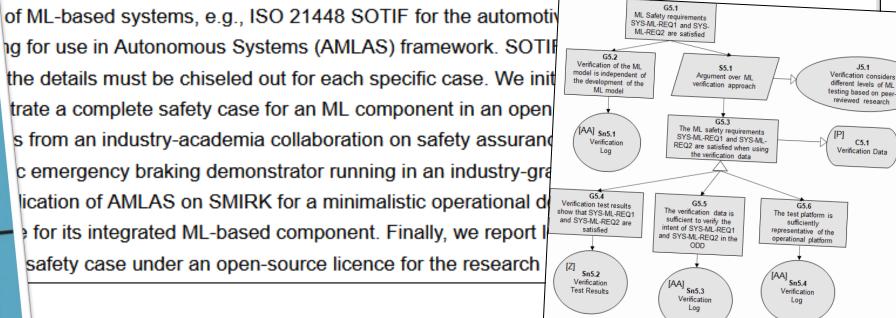
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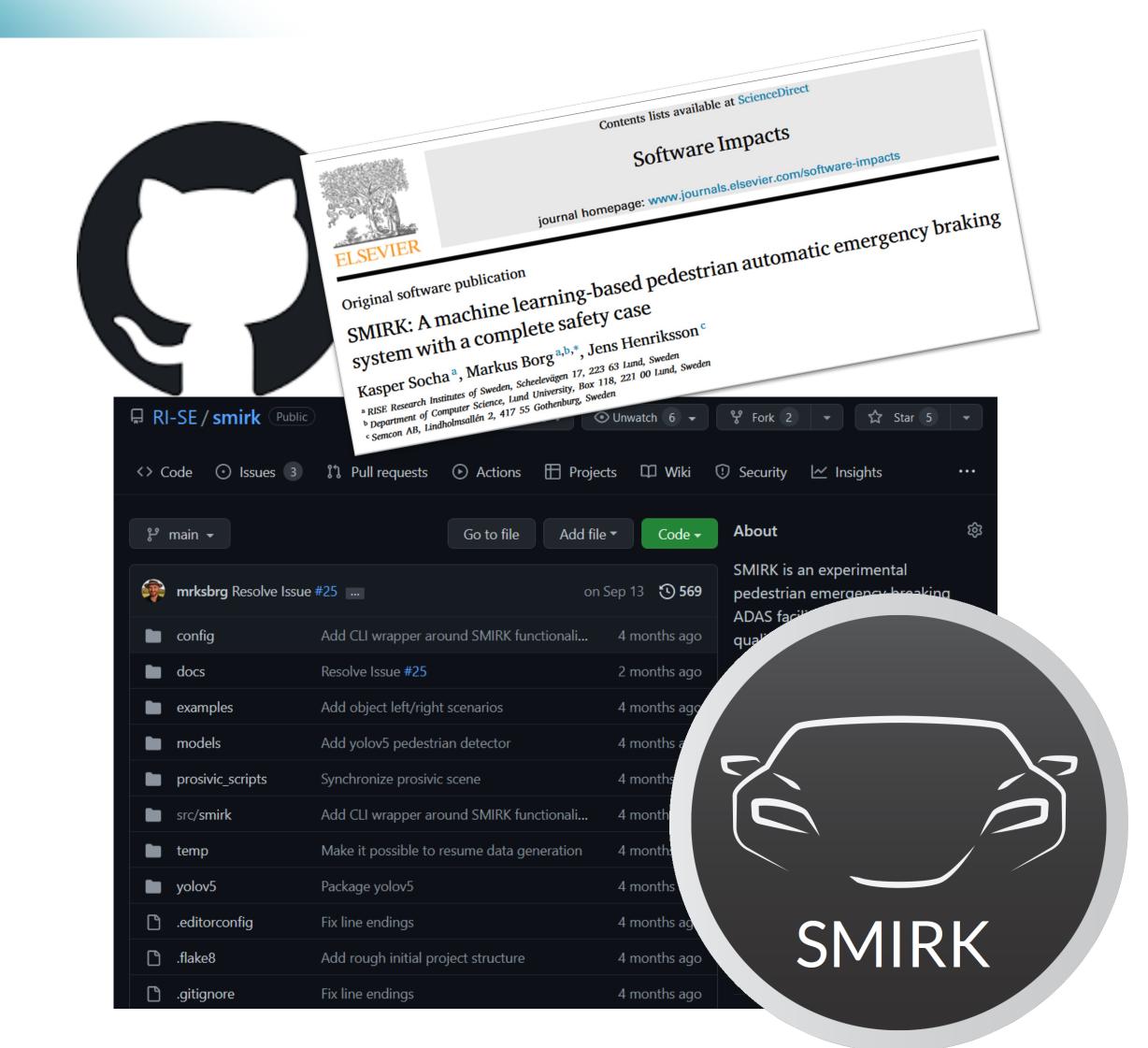
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Open ML-based demonstrator





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Requirements engineering for data

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Erc Co Technical debt in automotive software Mar Piot

markus.borg@codescene.com

Springer

Questions?





References

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- Data: https://www.ai.se/en/data-factory/datasets/data-factory-datasets/smirk-dataset
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Ben Abdessalem, Nejati, Briand, and Stifter, Testing Advanced Driver Assistance Systems Using Multi-objective Search and Neural Networks, In Proc. of the 31st