KI DATA TOOLING
The Data Kit for Automotive AI

KI Data Tooling Final Event | 05/06 December 2023

Deep Dive #4
Corner Case

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Jasmin Breitenstein - TUBS | Kamil Kowol - BUW

Corner Case Deep Dive

Agenda

1. Corner Case Taxonomy
2. Uncertainty-based Corner Case Detection
3. Context Information for Corner Case Detection
4. Corner Case Detection Pipeline
5. Corner Case Identification using Cameras and GPS
6. Amodal Semantic Segmentation
7. Relevance Estimation of Corner Cases
8. Driving with the Eyes of AI

Facts

- 22 Publications
- Partner:
  - Bosch
  - BMW (Fortiss)
  - BUW
  - FZI
  - TU Braunschweig
  - University of Kassel
  - ZF (FKA)

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Corner Case Taxonomy

What is a Corner Case ?

Software and Hardware Testing:

- Edge case, extreme case – testing extreme values of a parameter [1]
- Corner cases – rare or never considered combination of parameters [1]
- Test successfully passed – system verified

ML Viewpoint on Corner Cases:

- New situations or objects, … also considered as corner case
- Multiple samples of one corner case are needed for training or validation
- Sample is relevant for the task at hand

Multiple corner cases: A winter scene with an icy, slippery, reflective road, low winter sun and people on cross-country skis crossing the road. [2]

[1] P. Koopman, A. Kane, and J. Black, "Credible Autonomy Safety Argumentation," in Proc. of Safety-Critical Systems Symposium. Bristol, UK, 2019.
[2] F. Heidecker, J. Breitenstein, K. Rösch, J. Löhdefink, M. Bieshaar, C. Stiller, T. Fingscheidt, B. Sick, "An Application-Driven Conceptualization of Corner Cases for Perception in Highly Automated Driving", In Proc. of the IV, 2021.

Categorization of Camera-, LiDAR-, and RADAR-based Corner Cases

	Sensor Layer		Content Layer			Temporal Layer
	Hardware Level	Physical Level	Domain Level	Object Level	Scene Level	Scenario Level
LiDAR-based corner cases	Laser Error • *Broken mirror* • *Misaligned actuator*	Beam-Based Corner Case • *Black cars disappear* • ...	Domain Shift on Single Point Cloud • *Shape of Road markings*	Single-Point Anomaly on Single Point Cloud • *Dust cloud* • ...	Contextual/Collective Anomaly on Single Point Cloud • *Sweeper cleaning the sidewalk*	Corner Cases on Multiple Point Clouds and Frames • *Person breaks traffic rule* • *Overtaking a cyclist* • *Car accident* • ...
Camera-based corner cases	Pixel Error • *Dead pixel* • *Broken lense*	Pixel-Based Corner Case • *Dirt on lense* • *Overexposure*	Domain Shift on Single Frame • *Location (EU-U.S.A.)* • ...	Single-Point Anomaly on Single Frame • *Animal* • ...	Contextual/Collective Anomaly on Single Frame • *People on a billboard* • ...	
RADAR-based corner cases	Impulse Error • *Low voltage* • *Low temperature*	Impulse-Based Corner Case • *Interference* • ...	Domain Shift on Single Point Cloud • *Weather, e.g., snow, rain, etc.*	Single-Point Anomaly on Single Point Cloud • *Lost objects* • ...	Contextual/Collective Anomaly on Single Point Cloud • *Demonstration* • *Tree on street*	

Method-Layer:

- Corner cases of the method layer are caused by the applied methods
- Sensors or a human driver not necessarily perceive these corner cases
- Method layer corner cases are caused by uncertainty in the methodology

Examples for Method-Layer:

- High model uncertainty for unknown objects but also for typical normal objects
- Adversarial samples

F. Heidecker, J. Breitenstein, K. Rösch, J. Löhdefink, M. Bieshaar, C. Stiller, T. Fingscheidt, B. Sick, "An Application-Driven Conceptualization of Corner Cases for Perception in Highly Automated Driving", In Proc. of the IV, 2021.

Corner Case Generation

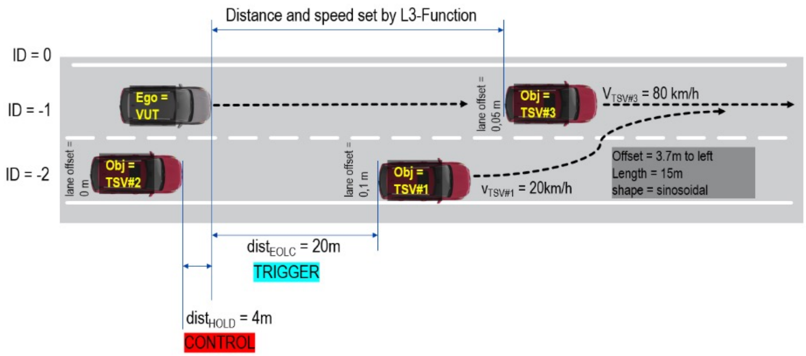
One Ontology to Rule Them All: Corner Case Scenarios for Autonomous Driving

§ 3

The manufacturer of a motor vehicle with an autonomous driving function shall **prepare a catalog of test scenarios.**

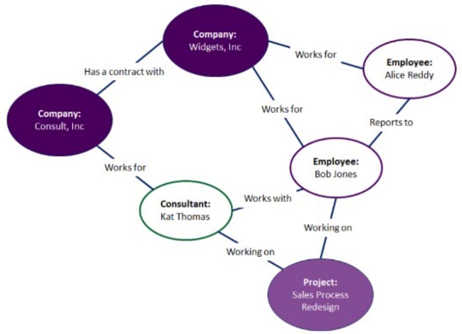
dserver.bundestag.de/brd/2022/0086-22.pdf

Code



releases.asam.net/OpenSCENARIO/2.0-concepts/ASAM_OpenSCENARIO_2-0_Concept_Paper.html

Ontology



enterprise-knowledge.com/what-is-an-ontology/

Expert knowledge in a machine- and human-readable way

Bogdoll, D., Guneshka, S., Zöllner, J.M. (2023). One Ontology to Rule Them All: Corner Case Scenarios for Autonomous Driving. ECCV 2022 Workshops

Corner Case Generation

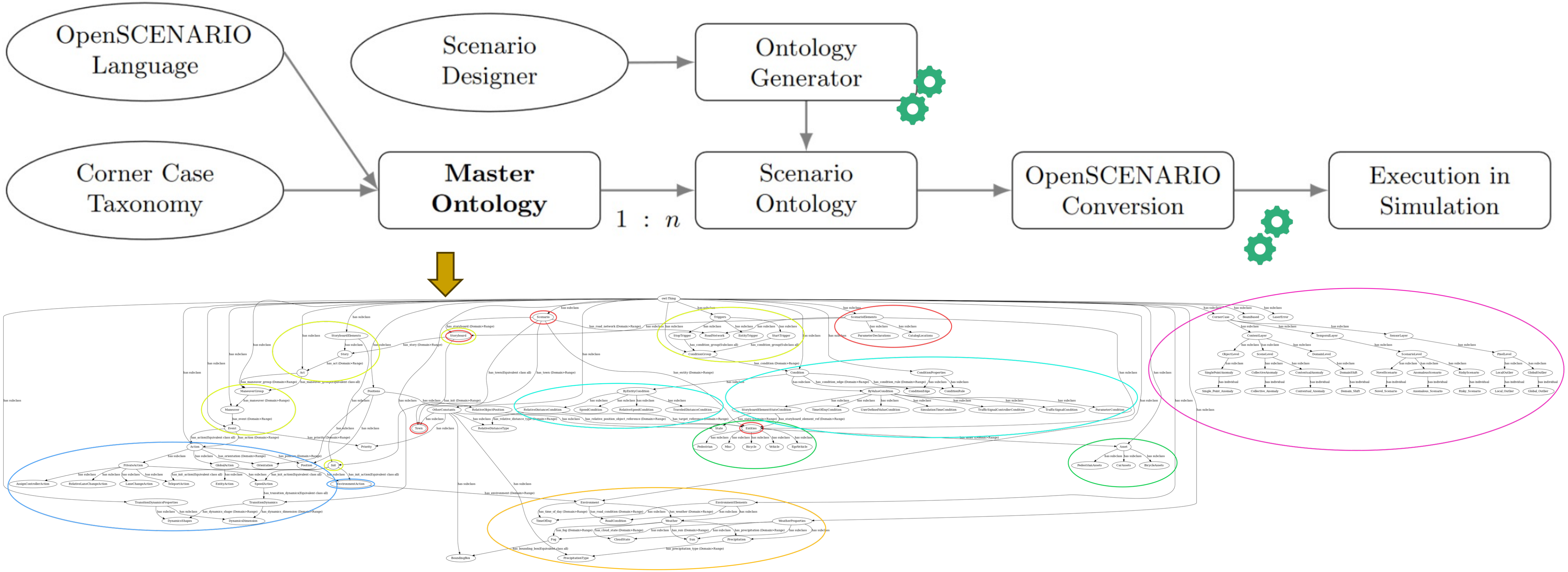
One Ontology to Rule Them All: Corner Case Scenarios for Autonomous Driving

Authors	Year	Temporal Scenario Description	Arbitrary Environments	Arbitrary Objects	Scenario Simulation	Corner Case Categorization	Ontology available
Fuchs et al. [16]	2008	-	-	✓	-	-	-
Hummel [25]	2010	-	✓	-	-	-	-
Hülsen et al. [26]	2011	✓	✓	-	-	-	-
Armand et al. [1]	2014	-	-	-	-	-	-
Zhao et al. [47]	2017	-	✓	-	-	-	✓
Bagschik et al. [5]	2018	✓	-	-	-	-	-
Chen and Kloul [13]	2018	✓	-	-	-	-	-
Huang et al. [24]	2019	✓	-	-	-	-	-
Menzel et al. [30]	2019	✓	✓	-	✓	-	-
Li et al. [29]	2020	✓	✓	-	✓	-	-
Tahir and Alexander [39]	2022	✓	-	-	✓	-	-
Hermann et al. [23]	2022	-	✓	✓	✓	-	-
ASAM [3]	2022	-	-	-	-	-	-
Proposed Ontology		✓	✓	✓	✓	✓	✓

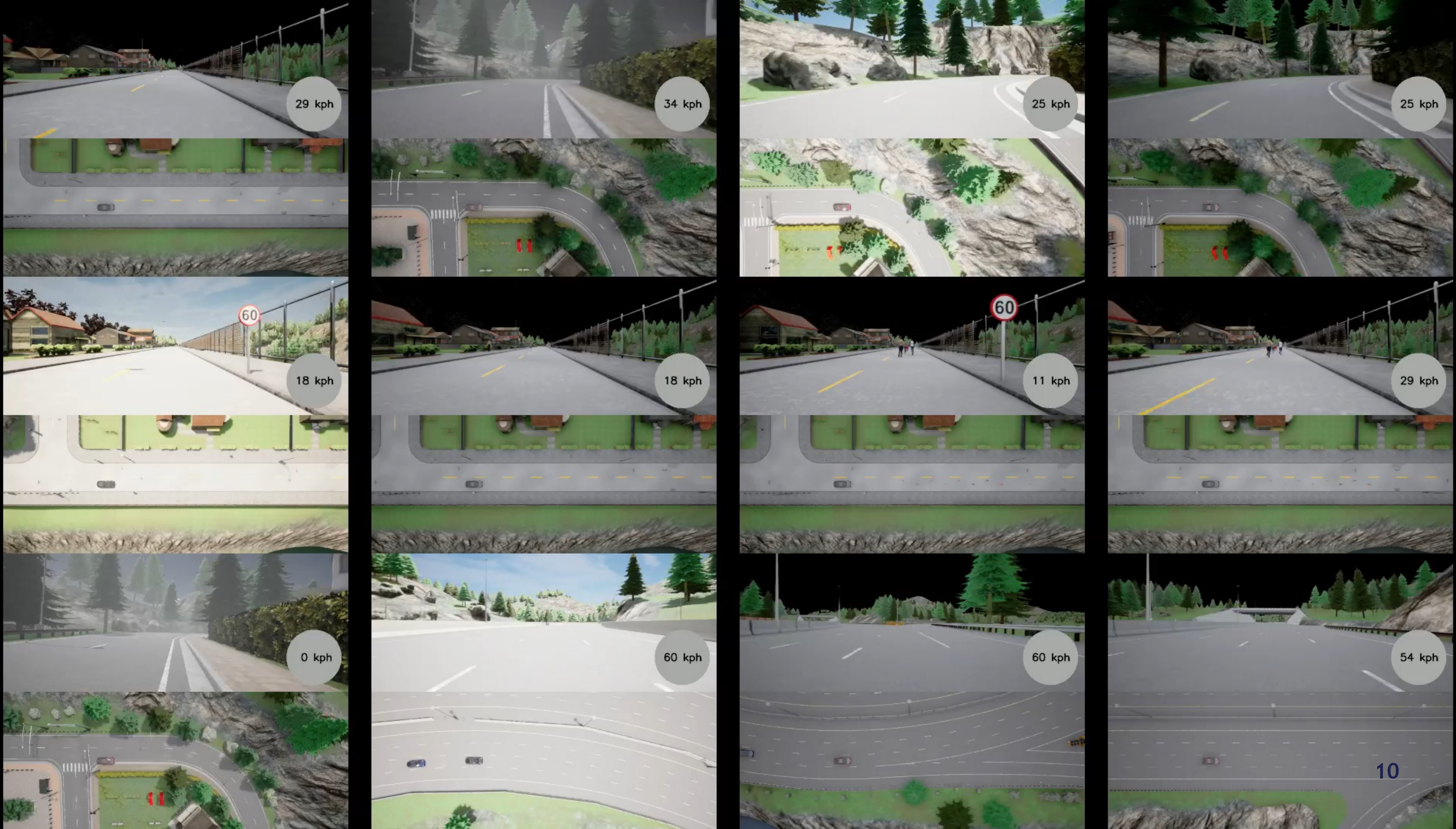
Bogdoll, D., Guneshka, S., Zöllner, J.M. , "One Ontology to Rule Them All: Corner Case Scenarios for Autonomous Driving," In Proc. of ECCV-Workshops, 2022.

Corner Case Generation

One Ontology to Rule Them All: Corner Case Scenarios for Autonomous Driving



Bogdoll, D., Guneshka, S., Zöllner, J.M. , "One Ontology to Rule ThemAll: Corner Case Scenarios for Autonomous Driving," In Proc. of ECCV-Workshops, 2022.


29 kph
34 kph
25 kph
25 kph
60
18 kph
18 kph
60
11 kph
29 kph
0 kph
60 kph
60 kph
54 kph

2

Uncertainty-based Corner Case Detection

Uncertainty-based Corner Case Detection

Goal:

- Identifying sample/corner cases where the model performs poorly in order to further improve the model

Challenges:

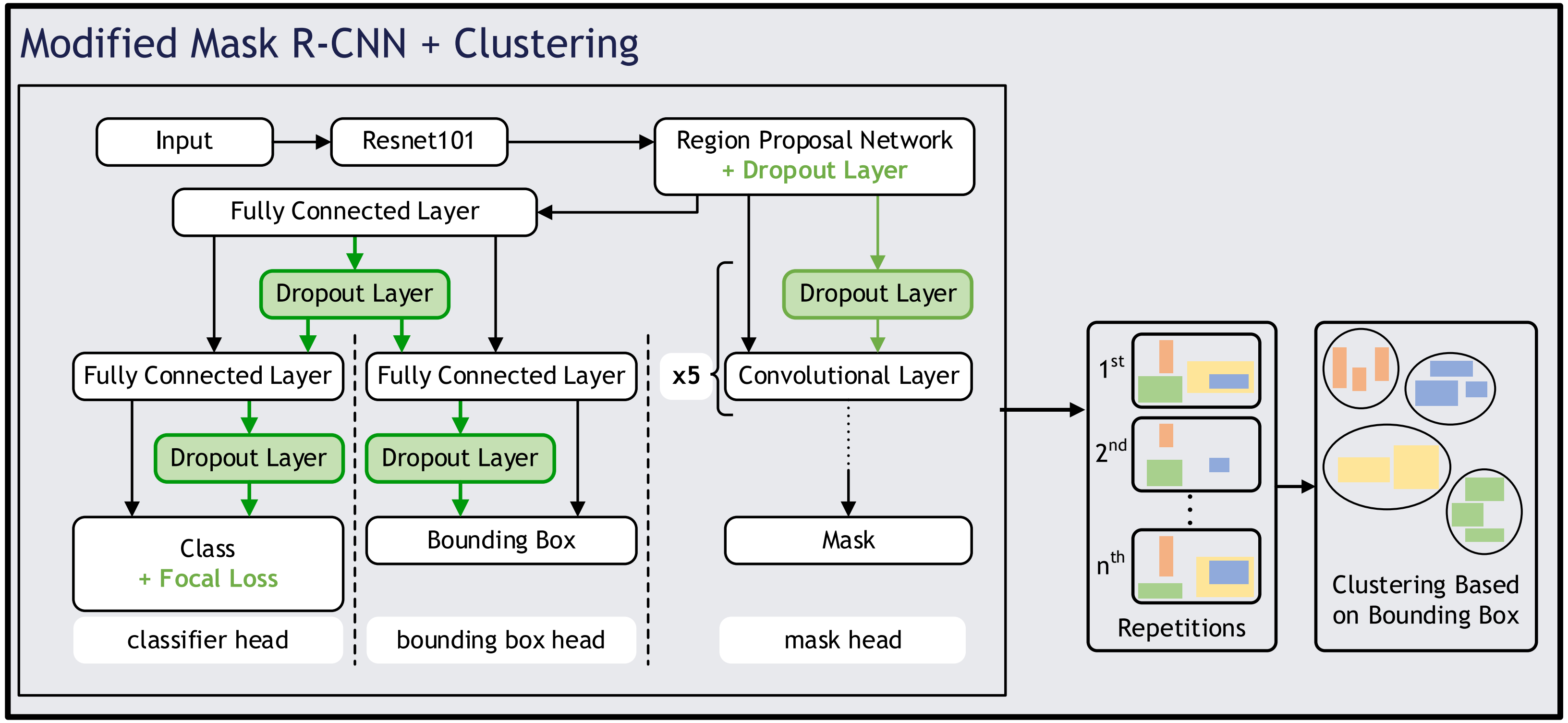
- Label information is not available at runtime
- Detecting corner cases based on the predictive uncertainty
- Classifying if the predictions are truth positive (TP), false negative (FN) or corner cases

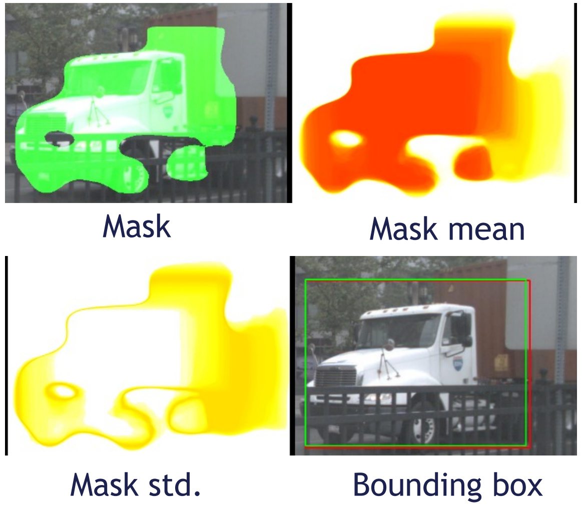
Poster

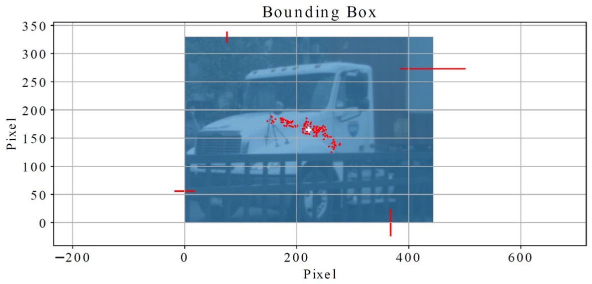
Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation

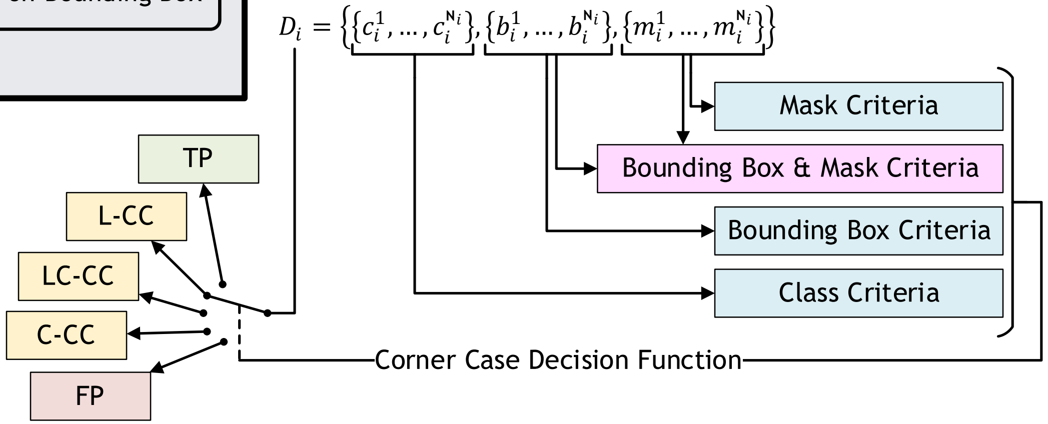
F. Heidecker, A. El-Khateeb, M. Bieshaar, B. Sick, *"Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation", (Review)*

Uncertainty-based Corner Case Detection Pipeline









F. Heidecker, A. El-Khateeb, M. Bieshaar, B. Sick, "Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation", (Review)

Corner Case Categories

- True Positive (TP): Class is correctly predicted, and IoU above 0.5.
- Corner Case:
  - Localization (L-CC):

    Class is correctly predicted, and IoU between 0.1 and 0.5.
  - Classification (C-CC):

    Class is wrong predicted, and IoU above 0.5.
  - Localization & Classification (LC-CC):

    Class is wrong predicted, and IoU between 0.1 and 0.5.
- False Positive (FP): All other detections.

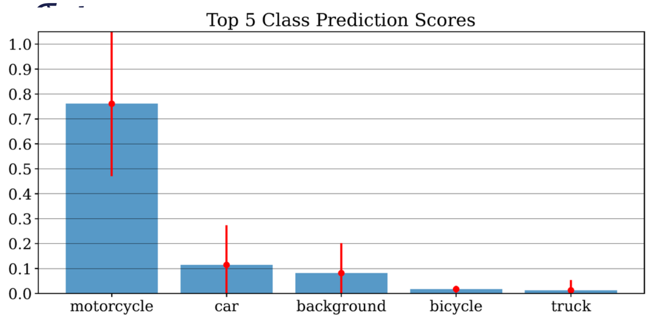
Dataset Details		COCO	NuImages
Size of Test Subset (Images)		4952	14884
Labeled Objects (Test Subset)		36335	136074
Model Predictions		68660	183597
TP	Correct Class & IoU > 0.5	23931 (34,9%)	104980 (57,2%)
L-CC	Correct Class & $0.5 >$ IoU > 0.1	2901 (4,2%)	7837 (4,3%)
C-CC	Wrong Class & IoU > 0.5	1766 (2,6%)	4134 (2,2%)
LC-CC	Wrong Class & $0.5 >$ IoU > 0.1	1257 (1,8%)	2846 (1,6%)
FP	No Matches	38805 (56,5%)	63800 (34,7%)
FN	Missed Objects	6480	16277
Bounding Box $mAP_{IoU>0.5}$		0.488	0.424
Mask $mAP_{IoU>0.5}$		0.467	0.366

F. Heidecker, A. El-Khateeb, M. Bieshaar, B. Sick, "Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation", (Review)

Uncertainty-based Corner Case Criteria

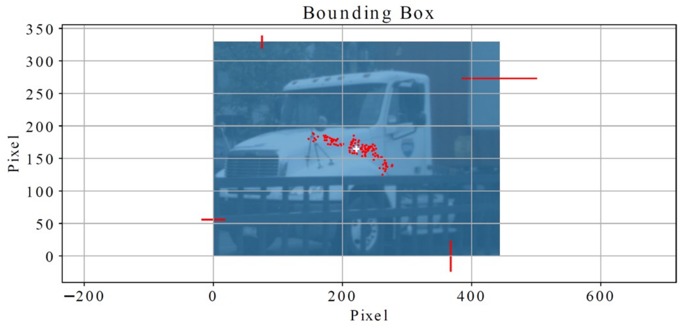
Class score criteria:

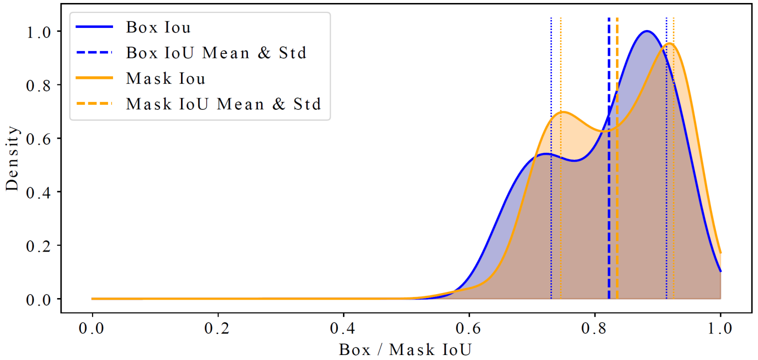
- $\overline{D_{c^{k_{\max}}}}$, $\sigma_{c^{k_{max}}}$, $\overline{D_{c^{k_{2nd\_max}}}}$,



Bounding box criteria:

- $\sigma^b_{x_1}$, $\sigma^b_{y_1}$, $\sigma^b_{x_2}$, $\sigma^b_{y_2}$, $\sigma^b_{c_x}$, $\sigma^b_{c_y}$, σ^b_{w}, σ^b_{h}
- $\overline{iou_b}$, σ_{iou_b}



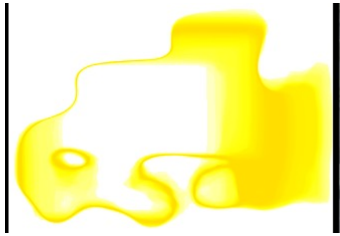


Mask criteria:

- $\sigma^m_{c_x}$, $\sigma^m_{c_y}$, σ^m_{w}, σ^m_{h}
- $\overline{iou_m}$, σ_{iou_m}
- σ_{A_m} (distribution of mask area)

Mask

Mask mean



Mask std.

Bounding box

Bounding box & mask criteria:

- $iou_{mismatch}$
- Kullback–Leibler divergence, Jensen-Shannon Distance, Earth Mover Distance

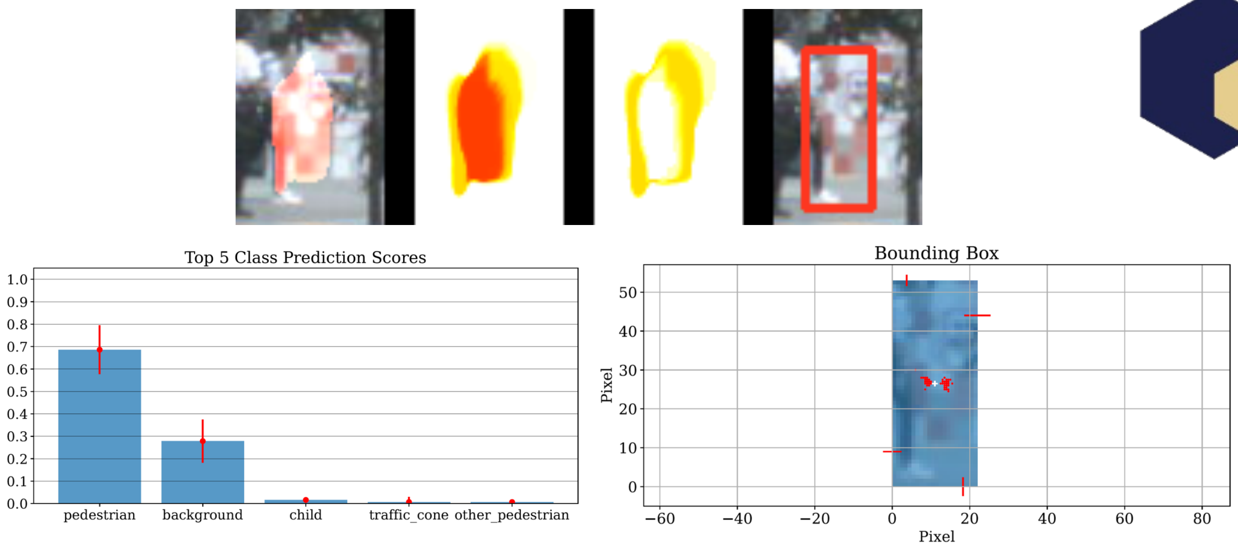
F. Heidecker, A. El-Khateeb, M. Bieshaar, B. Sick, “Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation”, (Review)

Corner Case Decision Function

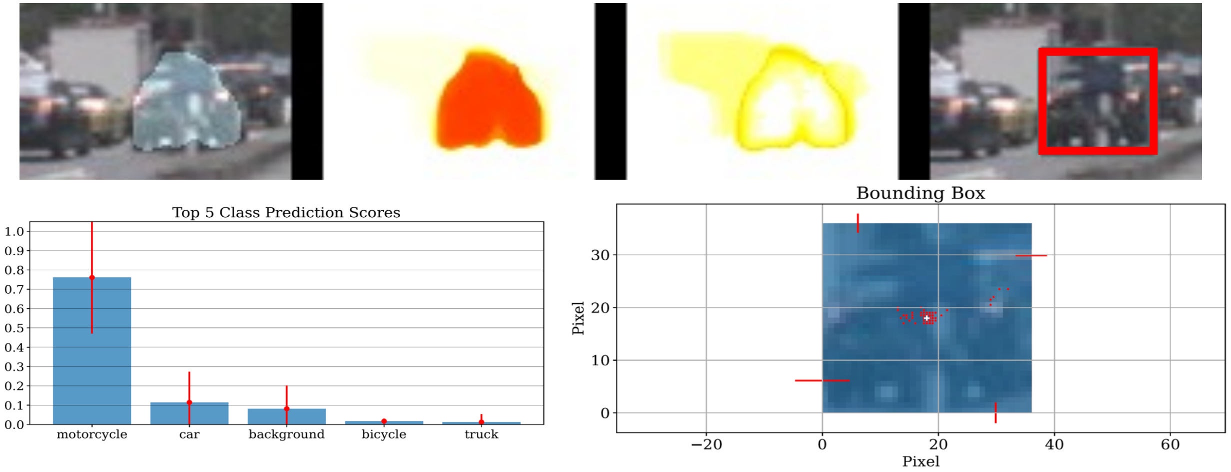
Multi-layer perceptron:

- Class-weighted f1 score: 0.449
- Confusion matrix

	TP	C-CC	L-CC	LC-CC	FP
TP	0.65	0.12	0.13	0.03	0.07
C-CC	0.26	0.42	0.08	0.13	0.11
L-CC	0.16	0.06	0.41	0.16	0.22
LC-CC	0.08	0.16	0.20	0.32	0.24
FP	0.09	0.12	0.23	0.21	0.35



Localization Corner Case (L-CC)



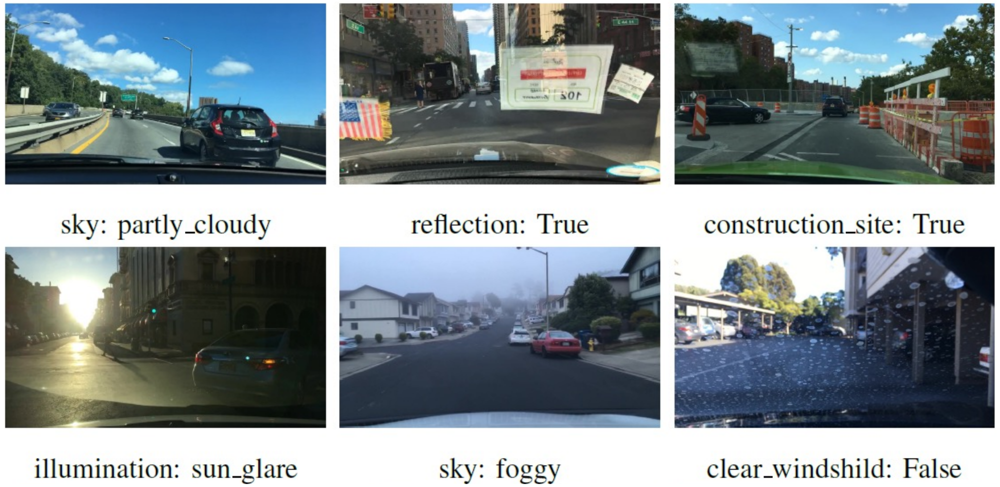
Classification Corner Case (C-CC)

F. Heidecker, A. El-Khateeb, M. Bieshaar, B. Sick, "Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation", (Review)

3

Context Information for Corner Case Detection

Context and Corner Cases



Example images from BDD100K[2] with different context attributes.

Context:

- Can be used to describe corner cases
- Diversity of dataset
- Facilitates data clustering
- Enables condition-based model evaluation

Is context useful to find corner cases?

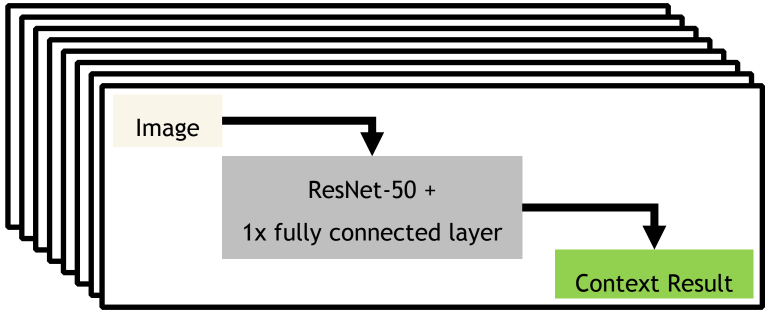
Time of day:	*daytime, dawn dusk, night, undefined*
Sky:	*clear, partly cloudy, overcast, foggy, undefined*
Illumination:	*natural, sun glare, artificial, dark*
Precipitation:	*nothing, rain, snow*
Infrastructure:	*inner city, industrial, highway, suburb, nature, parking lot, gas station, undefined*
Road:	*dry, wet, slushy, snowy, undefined*

Tunnel:	*true, false*
Construction site:	*true, false*
Clear windshield:	*true, false*
Light exposure:	*true, false*
Reflections:	*true, false*

[1] F. Heidecker, T. Susetzky, E. Fuchs, B. Sick, "Context Information for Corner Case Detection in Highly Automated Driving", In Proc. of ITSC, 2023.
[2] F. Yu, et al. , "BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning," in Proc. of CVPR, Seattle, WA, USA, 2020, pp. 2636-2645.

Context Annotation Procedure

1. First 10.000 BDD100K[1] images annotated and checked by a human, using CVAT[2]



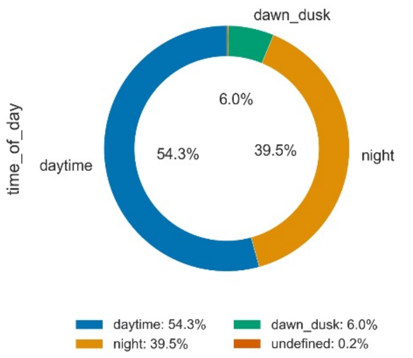
2. One model per context attribute: pre-training (with e.g., DENSE[3]) if possible and fine-tuning on already annotated BDD100K images

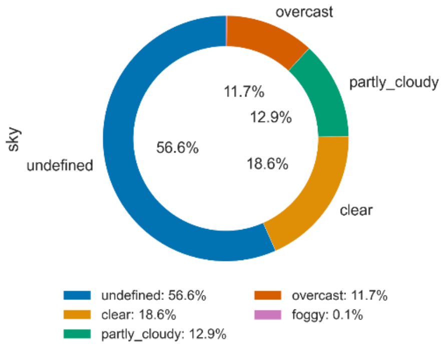
3. Automated pre-labeling of 10.000 BDD100K[1] images with our context model followed by visual annotation checks via humans

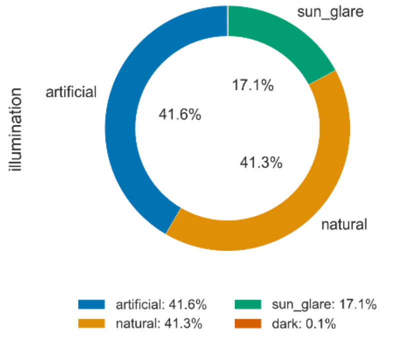
4. Context annotations cross checks, e.g., if perception “rain”, then road is “wet“

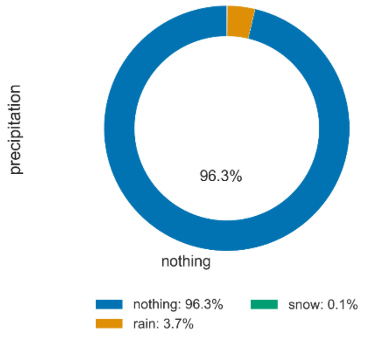
[1] F. Yu, et al. , “BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning,” in Proc. of CVPR, Seattle, WA, USA, 2020, pp. 2636-2645.
[2] Computer Vision Annotation Tool (CVAT), https://github.com/opencv/cvat
[3] M. Bijelic, et al. , “Seeing Through Fog Without Seeing Fog: Deep Multimodal Sensor Fusion in Unseen Adverse Weather,” in Proc. Of CVPR, Seattle, USA, 2020, pp. 11 682-11 692.

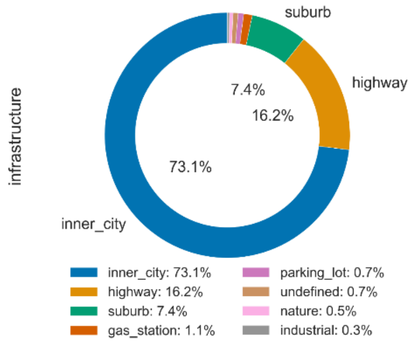
BDD100K Context Statistics

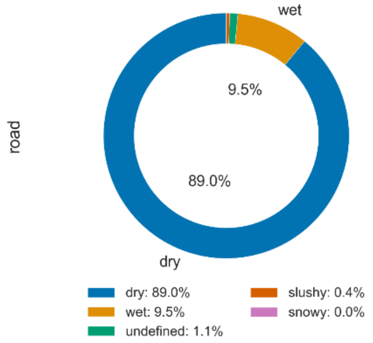


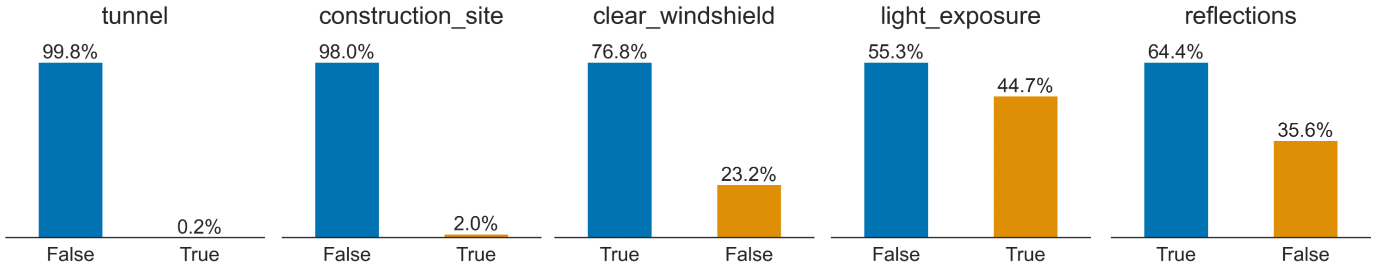


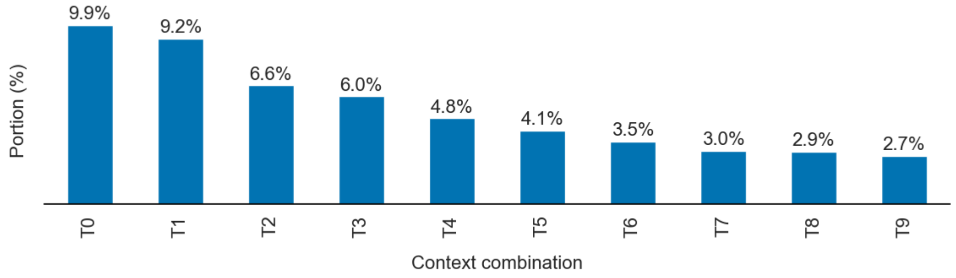












No.	Context Attribute						
	Infra.	Sky	ToD	ILL	LE	CW	Ref.
T0	inner_city	undefined	night	artificial	✓	✓	X
T1	inner_city	undefined	night	artificial	✓	✓	✓
T2	inner_city	undefined	daytime	sun_glare	X	✓	✓
T3	inner_city	clear	daytime	natural	X	✓	✓
T4	inner_city	undefined	night	artificial	✓	X	✓
T5	inner_city	partly_cloudy	daytime	natural	X	✓	✓
T6	inner_city	undefined	night	artificial	✓	X	X
T7	highway	undefined	night	artificial	✓	✓	X
T8	inner_city	overcast	daytime	natural	X	✓	✓
T9	inner_city	clear	daytime	natural	X	✓	X

common: tunnel: false, construction_site: false
precipitation: nothing, road: dry

Object Detection Performance

	mAP$_{50}$										
	All	I1	I1*	I2	I3	I4	I4*	I5	I5*	I6	I6*
TOOD	**50.0**	**48.0**		60.4	**67.4**	50.1		55.8		52.1	
Sparse R-CNN	**50.0**	45.6		62.9	67.3	**56.7**		**56.2**		**52.3**	
FreeAnchor	46.6	43.5		55.3	61.7	50.7		52.4		48.2	
DyHead	45.9	44.2		57.5	63.3	49.2		52.4		46.9	
RetinaNet	45.9	44.1		**65.1**	61.1	49.1		51.9		47.2	
FCOS	45.8	43.7		51.7	63.3	50.1		52.4		46.8	
Libra R-CNN	45.5	44.1		50.1	62.8	48.7		51.9		46.8	
DCNv2	45.4	43.2		62.0	63.0	48.3		52.3		46.3	
HRNet	45.3	42.2		54.4	60.7	48.1		52.2		46.3	
Cascade R-CNN	44.8	41.3		63.4	61.0	48.5		51.8		46.0	
Faster R-CNN	44.5	41.3		57.0	61.4	48.8		50.9		45.9	
CenterNet	44.4	42.6		53.0	61.3	49.6		51.0		45.5	
ATSS	43.4	39.9		51.4	58.0	44.6		49.9		44.8	
Model Mean	43.3	41.0		53.4	59.4	46.6		49.1		44.5	
YOLOv3	40.2	40.4		46.9	56.9	44.2		45.5		40.6	
EfficientNet	40.1	39.8		45.4	55.1	42.3		44.9		40.6	
YOLOF	39.8	38.6		44.6	53.4	38.2		44.5		40.4	
YOLOX-s	38.7	38.5		45.7	58.6	41.8		43.6		39.0	
DETR	34.0	30.4		47.5	46.9	33.3		37.7		36.6	
CornerNet	31.6	28.4		40.4	45.3	43.0		35.4		33.0	

- Pretrained 2D object detection models from MMDetection[2] and fine-tuned on BDD100K

Context	Samples	Description
I1/I1*	4007 / 192	time of day: night, illumination: artificial
I2	145	time of day: dawn dusk, illumination: artificial
I3	146	time of day: dawn dusk, illumination: sun glare
I4/I4*	242 / 154	time of day: dawn dusk, illumination: natural
I5/I5*	1614 / 138	time of day: daytime, illumination: sun glare
I6/I6*	3815 / 147	time of day: daytime, illumination: natural

[1] F. Heidecker, T. Susetzky, E. Fuchs, B. Sick, "Context Information for Corner Case Detection in Highly Automated Driving", In Proc. of ITSC, 2023.
[2] K. Chen, et. al, "MMDetection: Open MMLab Detection Toolbox and Benchmark," arXiv preprint arXiv:1906.07155, 2019.

Object Detection Performance

mAP$_{50}$											
	All	I1	I1*	I2	I3	I4	I4*	I5	I5*	I6	I6*
TOOD	**50.0**	**48.0**	73.8	60.4	**67.4**	50.1	56.7	55.8	**67.1**	52.1	63.1
Sparse R-CNN	**50.0**	45.6	**77.6**	62.9	67.3	**56.7**	**63.9**	**56.2**	65.2	**52.3**	**65.8**
FreeAnchor	46.6	43.5	73.8	55.3	61.7	50.7	57.8	52.4	66.3	48.2	56.8
DyHead	45.9	44.2	66.9	57.5	63.3	49.2	56.0	52.4	60.4	46.9	59.4
RetinaNet	45.9	44.1	70.5	**65.1**	61.1	49.1	54.9	51.9	60.3	47.2	62.4
FCOS	45.8	43.7	67.1	51.7	63.3	50.1	57.5	52.4	59.6	46.8	59.8
Libra R-CNN	45.5	44.1	71.6	50.1	62.8	48.7	55.9	51.9	60.2	46.8	58.0
DCNv2	45.4	43.2	71.3	62.0	63.0	48.3	54.0	52.3	60.3	46.3	61.8
HRNet	45.3	42.2	67.5	54.4	60.7	48.1	51.4	52.2	56.9	46.3	60.3
Cascade R-CNN	44.8	41.3	66.0	63.4	61.0	48.5	54.6	51.8	60.1	46.0	54.2
Faster R-CNN	44.5	41.3	66.2	57.0	61.4	48.8	54.4	50.9	51.1	45.9	54.1
CenterNet	44.4	42.6	65.7	53.0	61.3	49.6	55.7	51.0	58.9	45.5	58.9
ATSS	43.4	39.9	62.8	51.4	58.0	44.6	49.6	49.9	56.1	44.8	58.7
Model Mean	43.3	41.0	66.0	53.4	59.4	46.6	52.5	49.1	57.3	44.5	55.4
YOLOv3	40.2	40.4	65.4	46.9	56.9	44.2	48.6	45.5	53.3	40.6	49.0
EfficientNet	40.1	39.8	62.3	45.4	55.1	42.3	48.7	44.9	53.2	40.6	50.7
YOLOF	39.8	38.6	59.4	44.6	53.4	38.2	44.6	44.5	59.5	40.4	48.1
YOLOX-s	38.7	38.5	60.2	45.7	58.6	41.8	47.7	43.6	51.1	39.0	47.7
DETR	34.0	30.4	51.6	47.5	46.9	33.3	37.6	37.7	46.9	36.6	44.0
CornerNet	31.6	28.4	53.9	40.4	45.3	43.0	47.0	35.4	42.4	33.0	40.6

- Pretrained 2D object detection models from MMDetection[2] and fine-tuned on BDD100K
- Used subsampling (with respect to object size and number) to make subsets of context combinations comparable

Context	Samples	Description
I1/I1*	4007 / 192	time of day: night, illumination: artificial
I2	145	time of day: dawn dusk, illumination: artificial
I3	146	time of day: dawn dusk, illumination: sun glare
I4/I4*	242 / 154	time of day: dawn dusk, illumination: natural
I5/I5*	1614 / 138	time of day: daytime, illumination: sun glare
I6/I6*	3815 / 147	time of day: daytime, illumination: natural

[1] F. Heidecker, T. Susetzky, E. Fuchs, B. Sick, "Context Information for Corner Case Detection in Highly Automated Driving", In Proc. of ITSC, 2023.
[2] K. Chen, et. al, "MMDetection: Open MMLab Detection Toolbox and Benchmark," arXiv preprint arXiv:1906.07155, 2019.

Context Information for Corner Case Detection Summary

- Context can help to find Corner Cases.
- More data with diverse context combinations are required.
- Training and testing machine learning models with different context conditions.

- Additional context attributes[1] for the BDD100K dataset
  - Online available: https://doi.org/10.48662/daks-25

Poster Context Information for Corner Case Detection in Highly Automated Driving

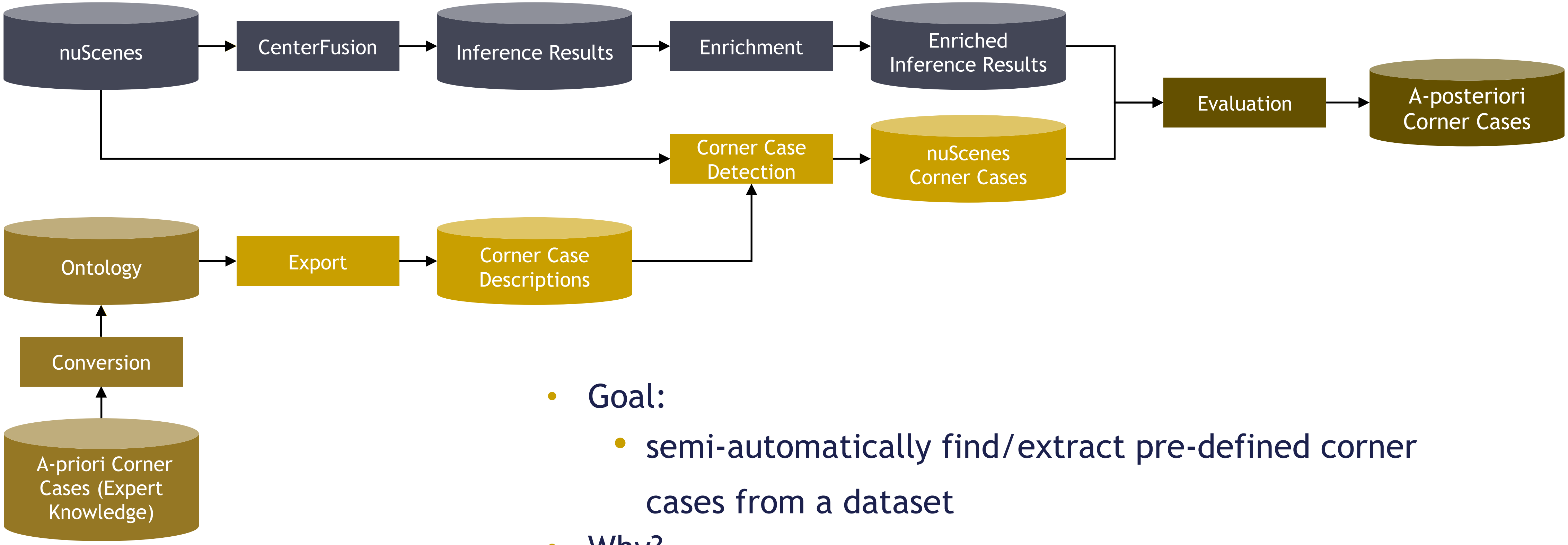
Example images from BDD100K[2] with different context attributes.

[1] F. Heidecker, T. Susetzky, E. Fuchs, B. Sick, "Context Information for Corner Case Detection in Highly Automated Driving", In Proc. of ITSC, 2023.
[2] F. Yu, et al. , "BDD100K: A Diverse Driving Dataset for Heterogeneous Multitask Learning," in Proc. of CVPR, Seattle, WA, USA, 2020, pp. 2636-2645.

4

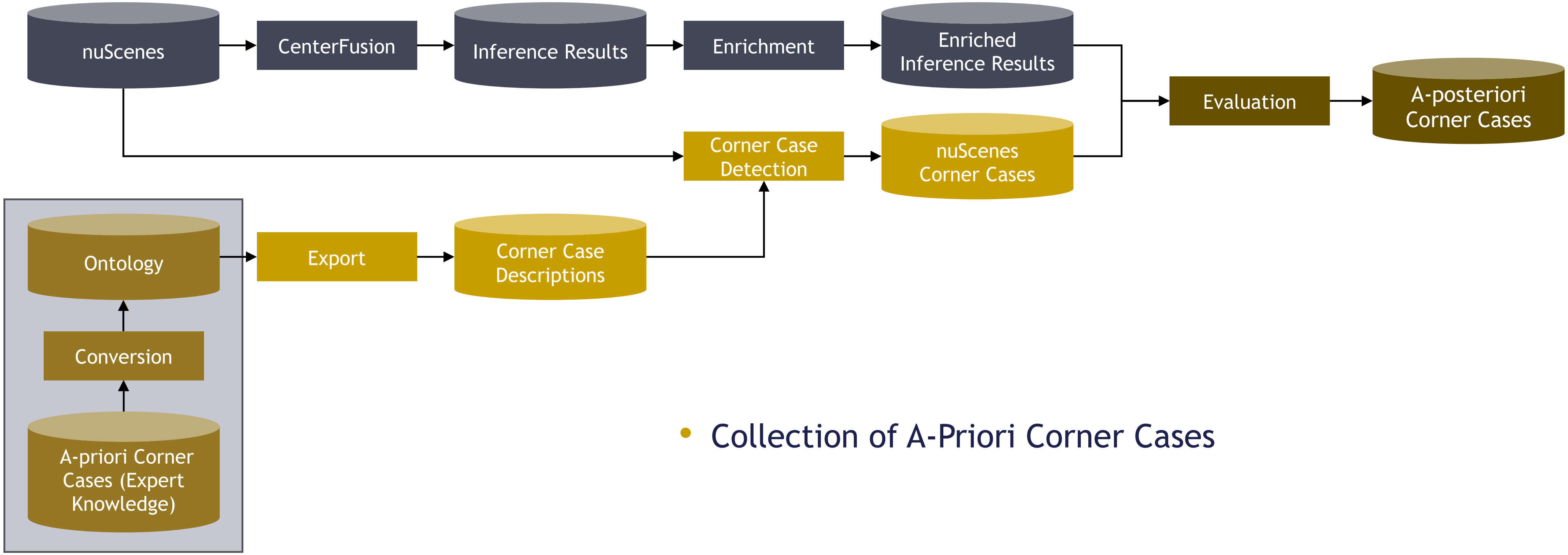
Corner Case Detection Pipeline

Pipeline Corner Cases



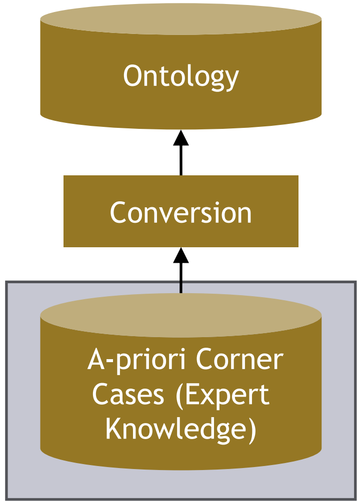
- Goal:
  - semi-automatically find/extract pre-defined corner cases from a dataset
- Why?
  - evaluate the performance of a detection network
  - define corner case descriptions to create synthetic data

Pipeline Corner Cases



- Collection of A-Priori Corner Cases

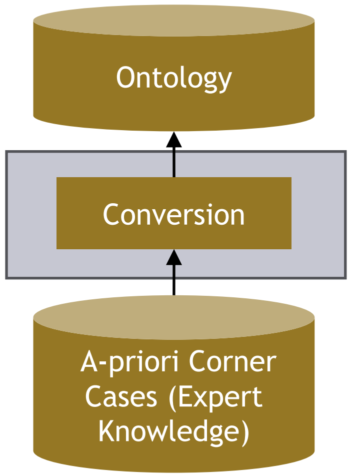
A-Priori Corner Cases



- Collect known (perception) corner cases from
  - KI-DT knowledge
  - Papers
  - Experts
- Maintain knowledge in excel list with the following information
  - Description and Cause
  - Sensor Source (Radar, Lidar, Camera) and Fusion
  - Layer and Level

Relevanc e for erceptio	Description	Cause	Effect	RaVioLi	Fusion	Source	Layer	Level
High	Small reflection surface	Small objects, angle to radar to small, distance to radar to high	Not detected by radar	R	No	single	Sensor	Physical - LocalOutlier
High	Coverage of radar sensor	snow, leaves	no data in (parts of) points cloud	R	No	single	Content	Domain
High	Change in pitch angle/elevation, high pitch angle	slopes, curvature, acceleration, braking, uneveness of road, dips in road, winding roads, (up/down) hill drive	objects out of FoV, reflections from road	R	No	single	Sensor	Physical - Global Outlier
High	Diffraction of waves	crests in road	look through objects	R	No	single	Sensor	Physical - Global Outlier
High	heigh objects, e.g. metal bridge	Small vertical opening angle	overhead structures classfied on road	R	No	single	Content	Object
High	Flat objects, e.g. trailers, back of towing trucks	Small vertical opening angle	Not detected by radar	R	No	single	Content	Object
		Access ladder on trucks, manhole covers, plates, marking						

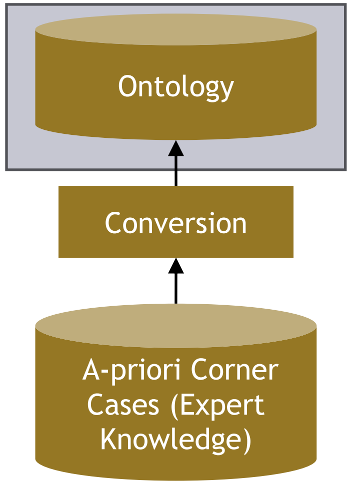
A-Priori Corner Cases

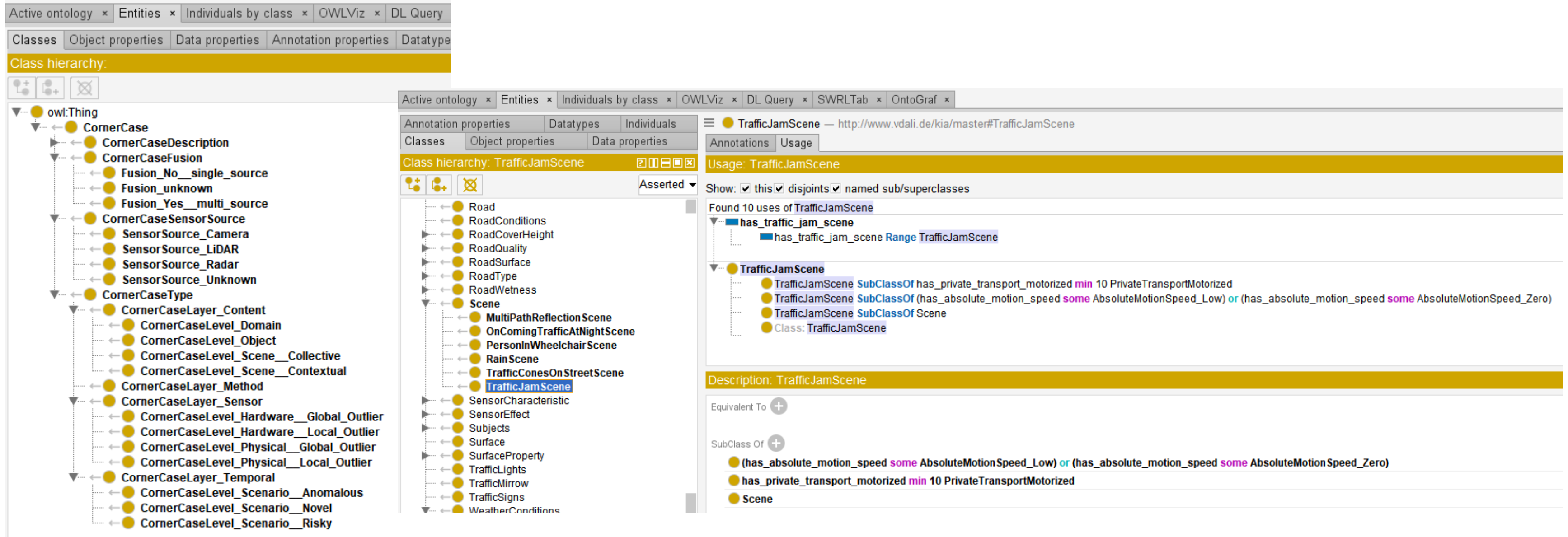


- Collect known (perception) corner cases
- Maintain knowledge in excel list
- Describe Corner Cases in Ontology
  - Convert script-based all information in excel list
    - Layer, level, source, fusion, description, cause
  - Describe Scene manual
    - One Scene for each corner case
    - All information in scene relevant for corner case
    - All non-set properties can be varied arbitrary without loosing the corner case

A-Priori Corner Cases

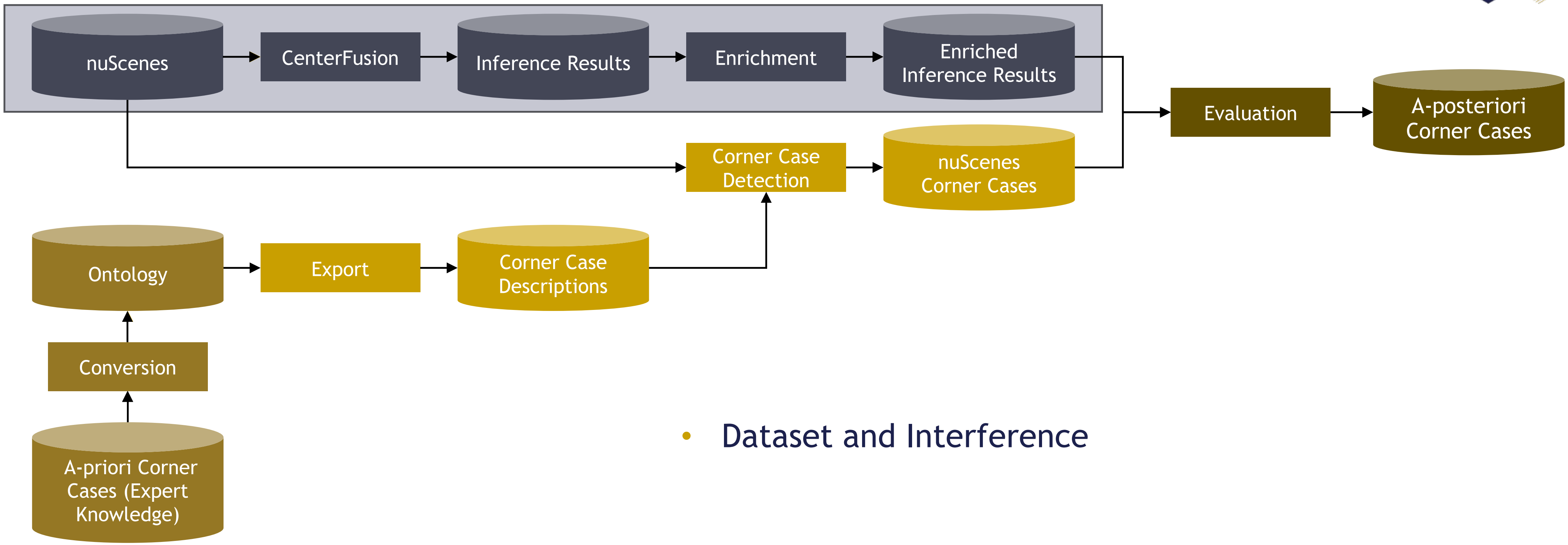
- Collect known (perception) corner cases
- Maintain knowledge in excel list
- Describe Corner Cases in Ontology
- Use existing KIA-Ontology[1] (KI Absicherung) as basis
    - Create new sub-ontology for general corner case properties





[1] *“Using ontologies for dataset engineering in automotive AI applications M.Herrmann, C. Witt, L. Lake, S. Guneshka, C. Heinzemann, F. Bonarens, P. Feifel, S. Funkeln 2022 Design, Automation & Test in Europe Conference & Exhibition (DATE), pp. 526-531. IEEE, 2022.*

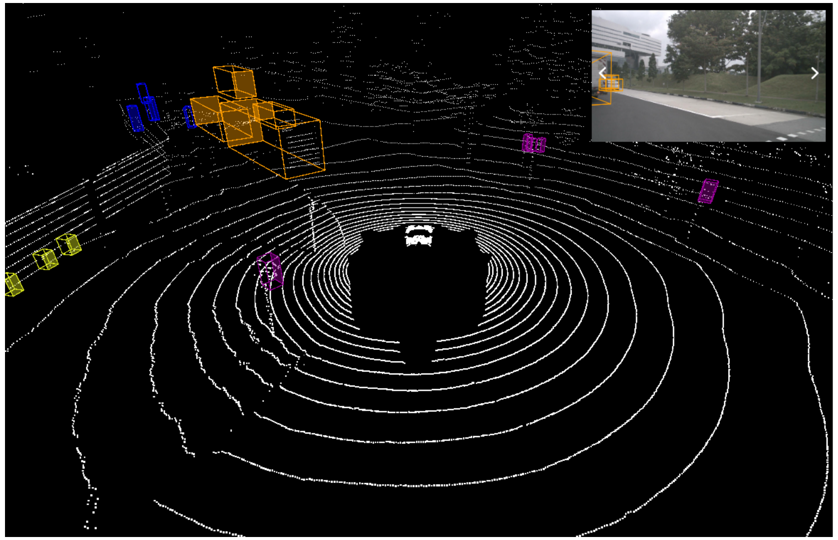
Pipeline Corner Cases

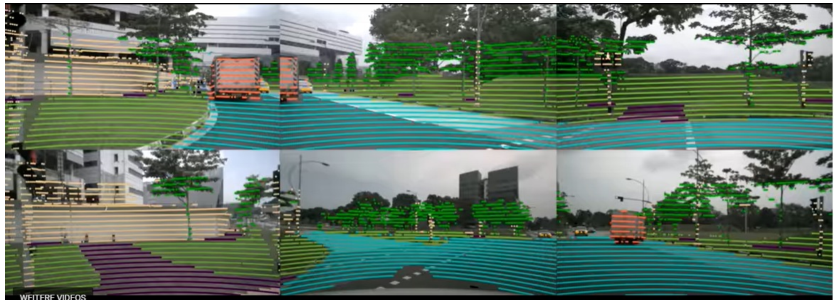


- Dataset and Interference

Dataset and Inference

nuScenes[1] → CenterFusion → Inference Results → Enrichment → Enriched Inference Results



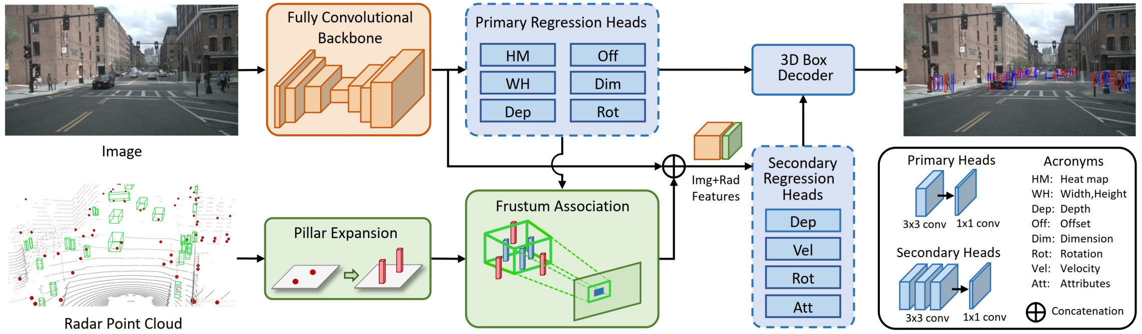


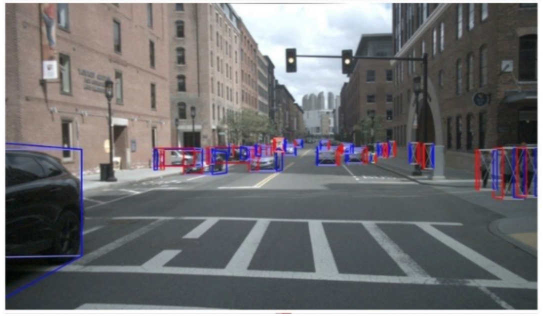
- 1000 scenes with 20s each
  - Labeled in 2Hz → 40 keyframes per scene
  - 850 scenes for training and validation
  - 150 scenes for testing (test dataset not available)
- Included information:
  - 23 labeled classes
  - Object attributes like visibility, activity and pose
  - Sensor data
  - Scene description by human expert

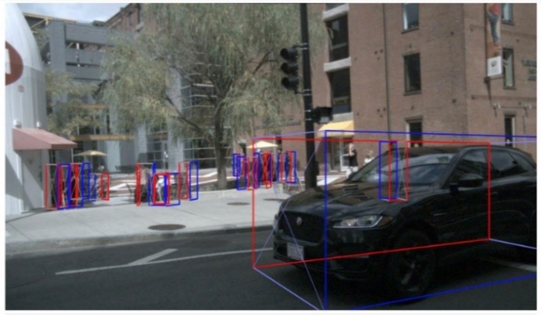
[1] H. Caesar, V. Bankiti, A. H. Lang, S. Vora, V. E. Liong, Q. Xu, A. Krishnan, Y. Pan, G. Baldan and O. Beijbom, "nuScenes: A multimodal dataset for autonomous driving", In Proc. of CVPR, 2020.

Dataset and Inference

- 3D Object Detection using radar and camera
  - Fusion of sensor features
  - Trained on train/validation nuScenes dataset
  - Mean average precision (mAP) test dataset: 0.326
- We used the pretrained network to get inference results of the validation set
  - Limited validity
  - Test dataset not available



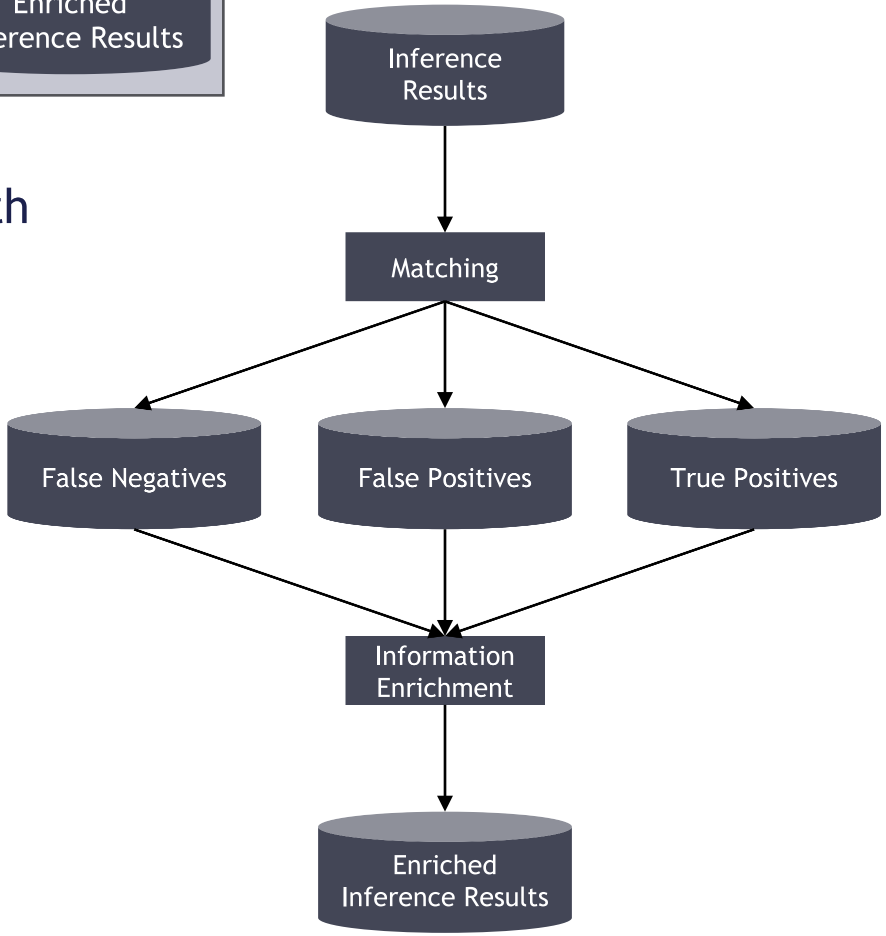




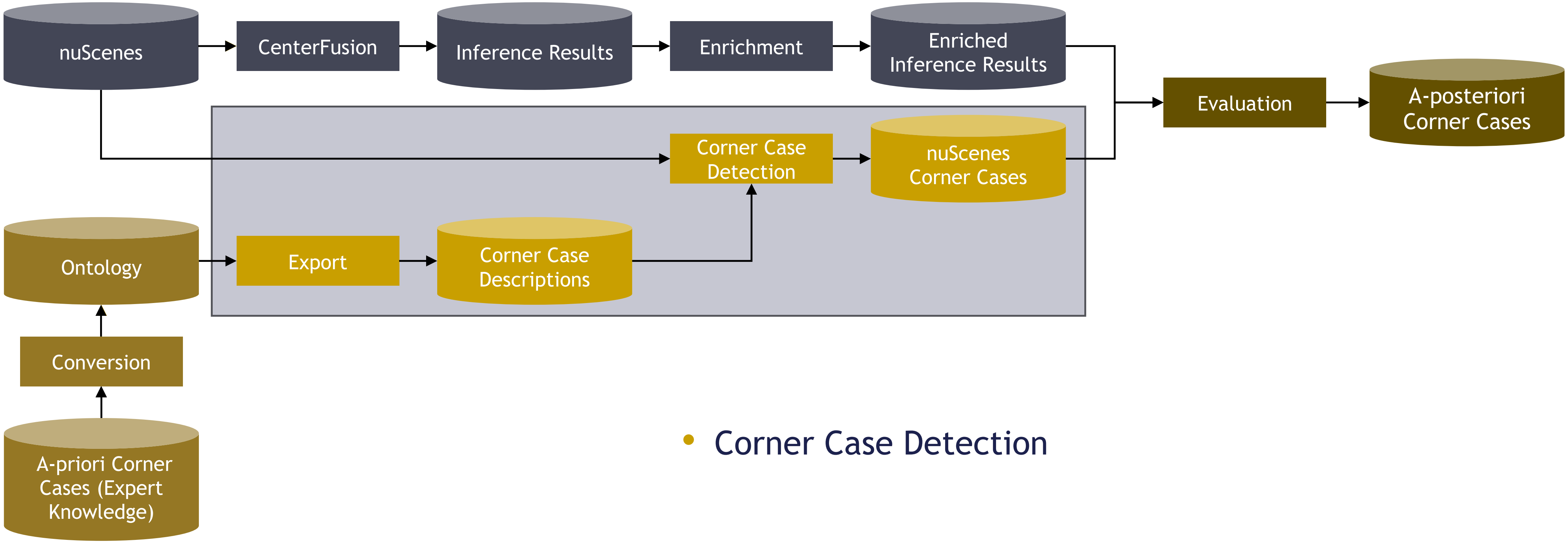
[1] *R. Nabati and H. Qi, "CenterFusion: Center-based Radar and Camera Fusion for 3D Object Detection," In Proc. of WACV*, Waikoloa, HI, USA, 2021.

Dataset and Inference

- Matching between predicted bounding boxes and ground truth
- Collect all “FN”, “FP” and “TP” for each sample
- Enrichment of relevant information:
  - Unique hash tokens of each detection
  - All available detection object information
    - Visibility, pose and size, timestamp and class
  - Scene description

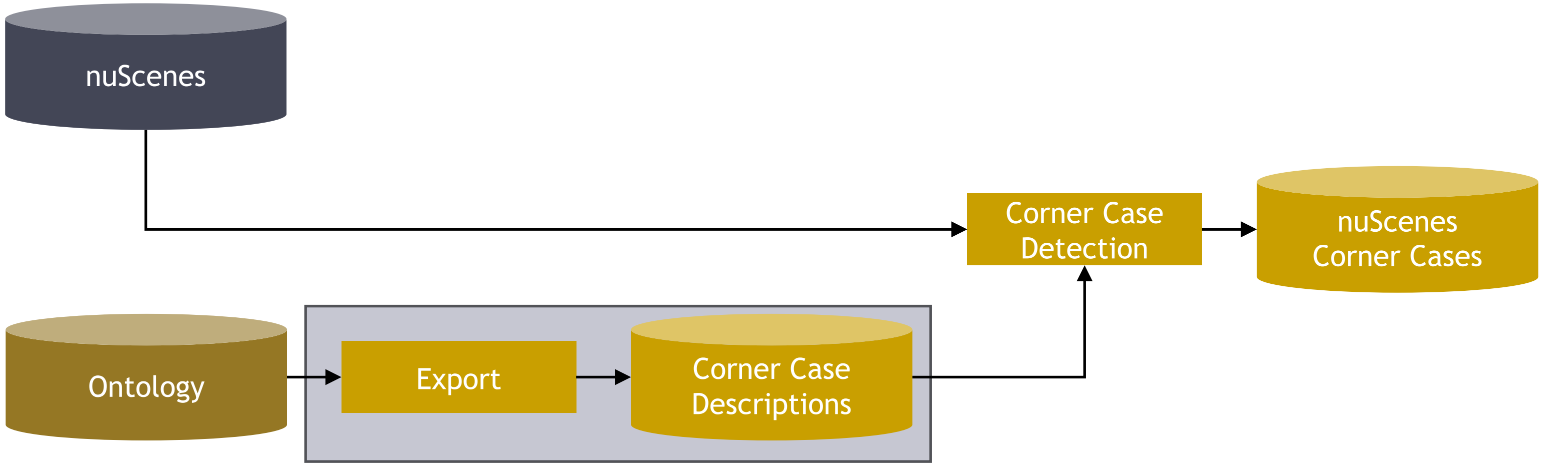


Pipeline Corner Cases



- Corner Case Detection

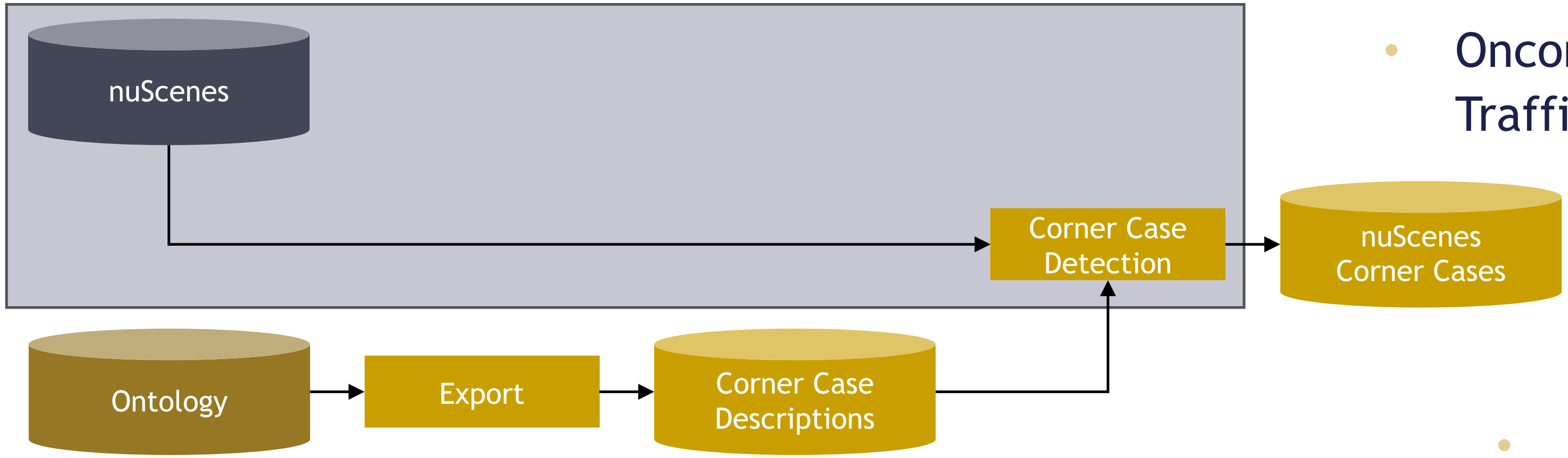
Corner Case Detection



- Export information in ontology to use in data set
- User provides mapping between ontology information and descriptions in data set (e.g. labeling information, where data is stored etc.)
- Result File contains
  - Meta-Information of Corner Case
  - Metric how to find Corner Case in data set


```
"corner_cases": [
  {
    "id": 1,
    "description": "CCDes__Camera_Overexposure__light_of_oncoming_traffic_at_night",
    "ravioli": "Vision",
    "fusion": "false",
    "source": "single",
    "types": [
      {
        "layer": "Sensor",
        "level": "Physical: Global Outlier"
      }
    ],
    "metrics": [
      {
        "scenario_descriptions": [
          "night"
        ],
        "elements": [
          {
            "relevant_classes": [
              "bus"
            ],
            "class_properties": [
              {
                "DistanceToEgo": {
                  "min": 15.0,
                  "max": 80.0,
                  "unit": "m"
                }
              },
              {
                "OrientationToEgo": {
                  "min": 150.0,
                  "max": 210.0,
                  "unit": "degree"
                }
              }
            ]
          }
        ]
```

Corner Case Detection



- Export information in ontology to metrics for search in dataset
- Browse nuScenes according to metrics
- Collect scenes, samples and object that belong to metric

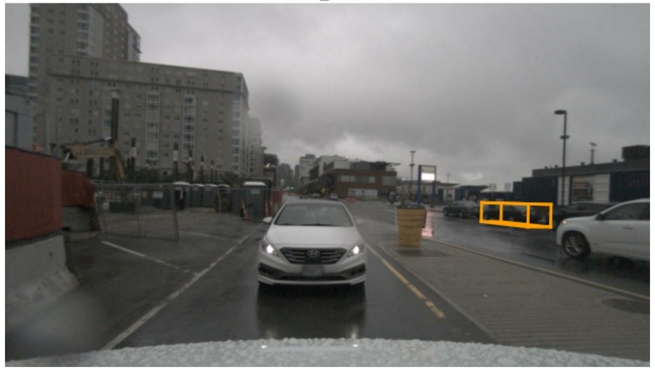
- Oncoming Traffic at night

CAM_FRONT

- Traffic Cones

CAM_FRONT

CAM_BACK

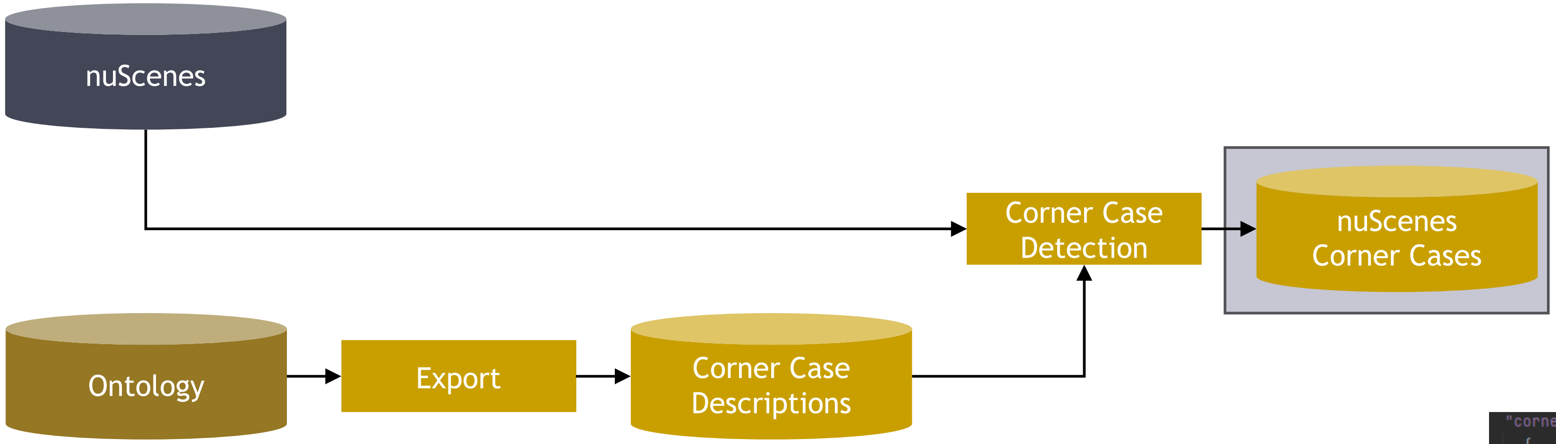


- Rain

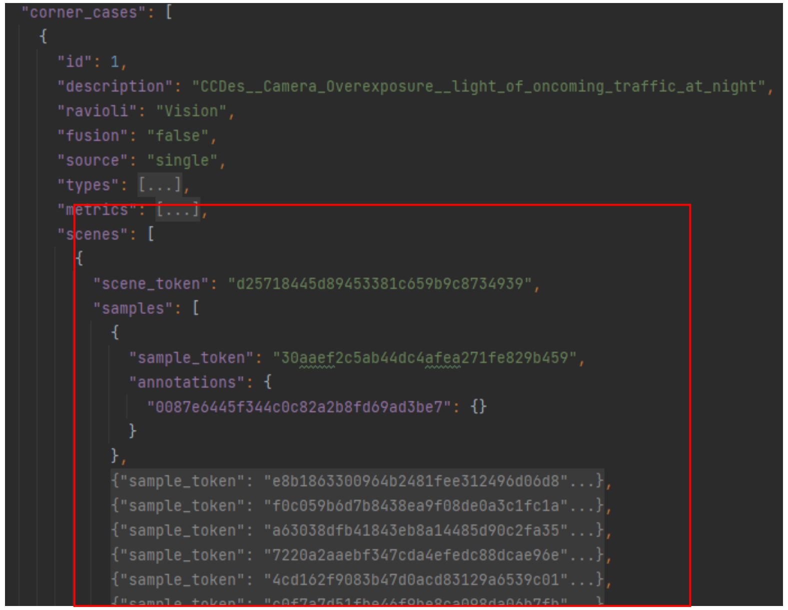
- Traffic Jam

CAM_FRONT

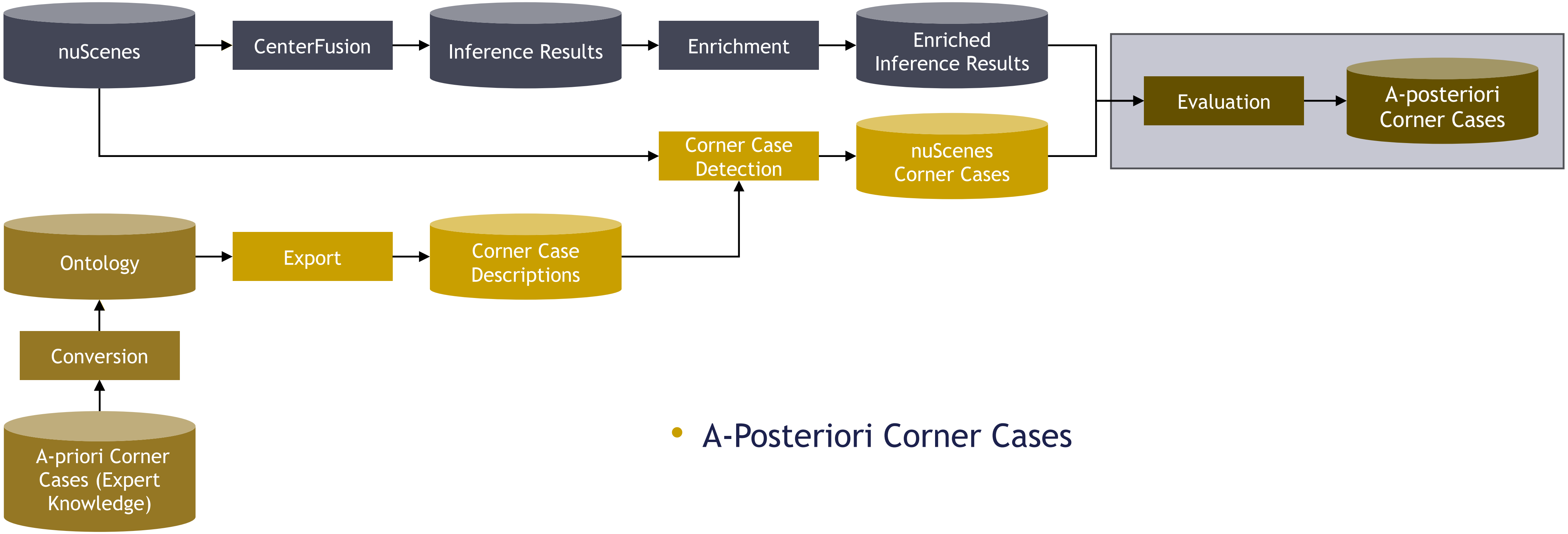
Corner Case Detection



- Export information in ontology to metrics for search in dataset
- Browse nuScenes according to metrics
- Collect scenes, samples and object that belong to metric
- Result File
    - Contains all information from corner case description
    - Contains all scene, samples and objects that belong to this corner case



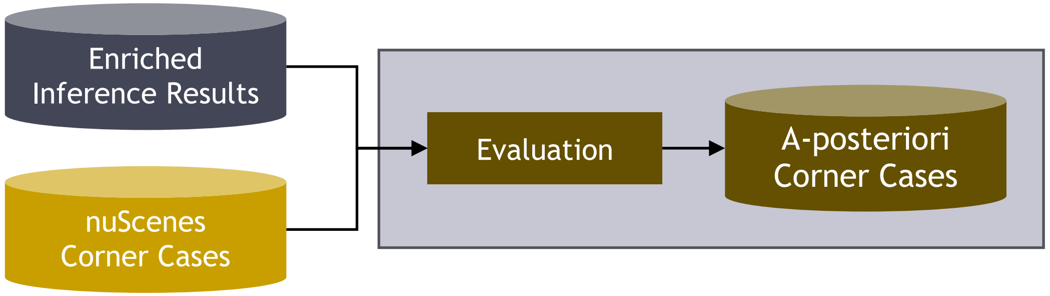
Pipeline Corner Cases



- A-Posteriori Corner Cases

A-Posteriori Corner Cases


```
"corner_cases": [
  {
    "id": 1,
    "description": "CCDes__Camera_Overexposure__light_of_oncoming_traffic_at_night",
    "ravioli": "Vision",
    "fusion": "false",
    "source": "single",
    "types": [...],
    "metrics": [...],
    "scenes": [
      {
        "scene_token": "e8099a6136804f3bb9b38ff94d98eb64",
        "samples": [
          {
            "sample_token": "79f6489272c24d3ebc5e225ce6ff2aea",
            "annotations": {
              "e5370d1340e14e4d84fb137e03547c35": {
                "status": "false_negative",
                "info": {"token": "e5370d1340e14e4d84fb137e03547c35"...}
              }
            }
          },
          {"sample_token": "caa701c185b94d9f948883bd65be2cd3"...},
          {"sample_token": "bb4f3cfb564f47a3bb9b9313e19365c2"...},
          {"sample_token": "d1d38dddb8174acf9cb776ec6c941024"...},
          {"sample_token": "b2f43ac0111945a3b3b08af102d2a8ab"...},
          {"sample_token": "42060e0081f249d7bcb5d2a0aa4e980a"...},
          {"sample_token": "50f1c83c63ec40fcae6615e8a6a19a23"...}
```

- Evaluate inference results and found corner cases
  - Check for every object in a corner case if it is an actual corner case or not
  - Add result to each corner case object together with object information (class, size, translation, …)
- The resulting file can be used to generate statistics

Results

- Corner Cases in nuScenes validation set:
  - Objects: 32.819 of total 122.778 (27%)
  - Samples: 2025 of total 6019 (34%)
  - Scenes: 83 of total 150 (55%)

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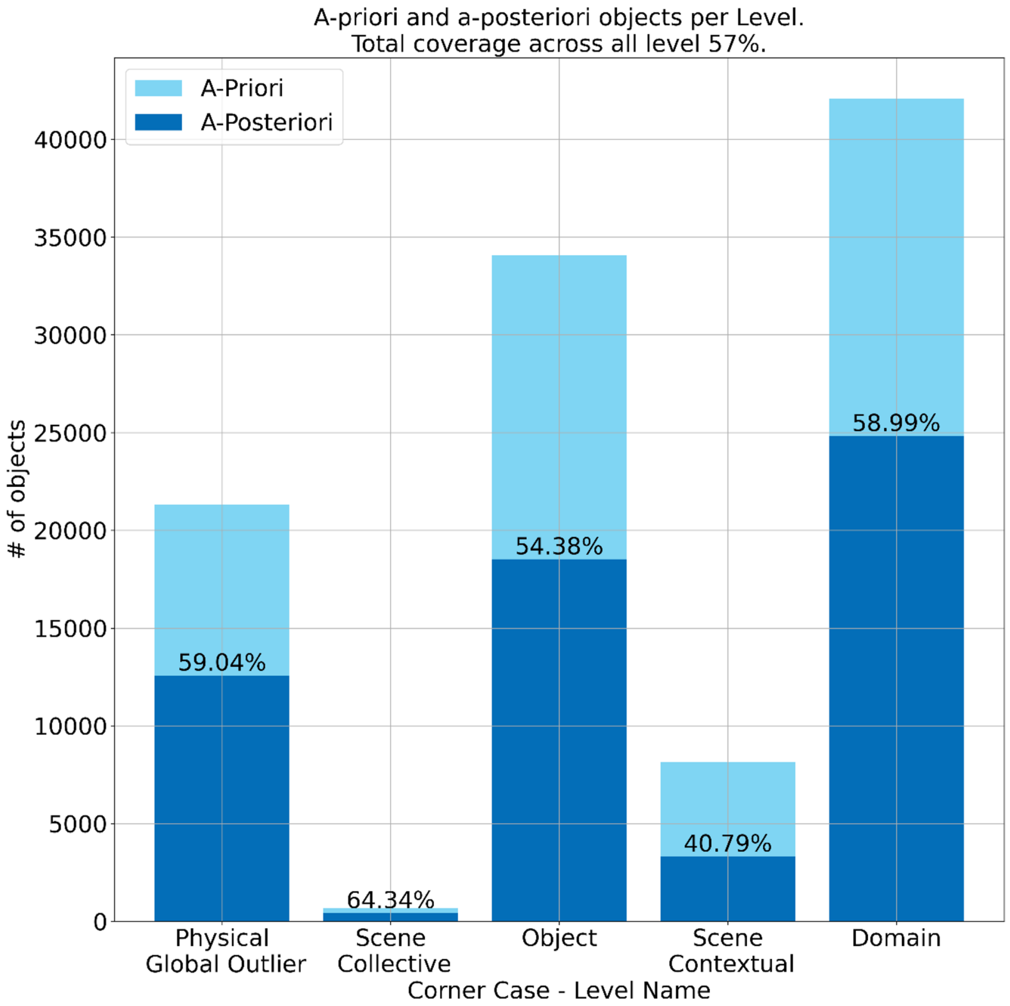

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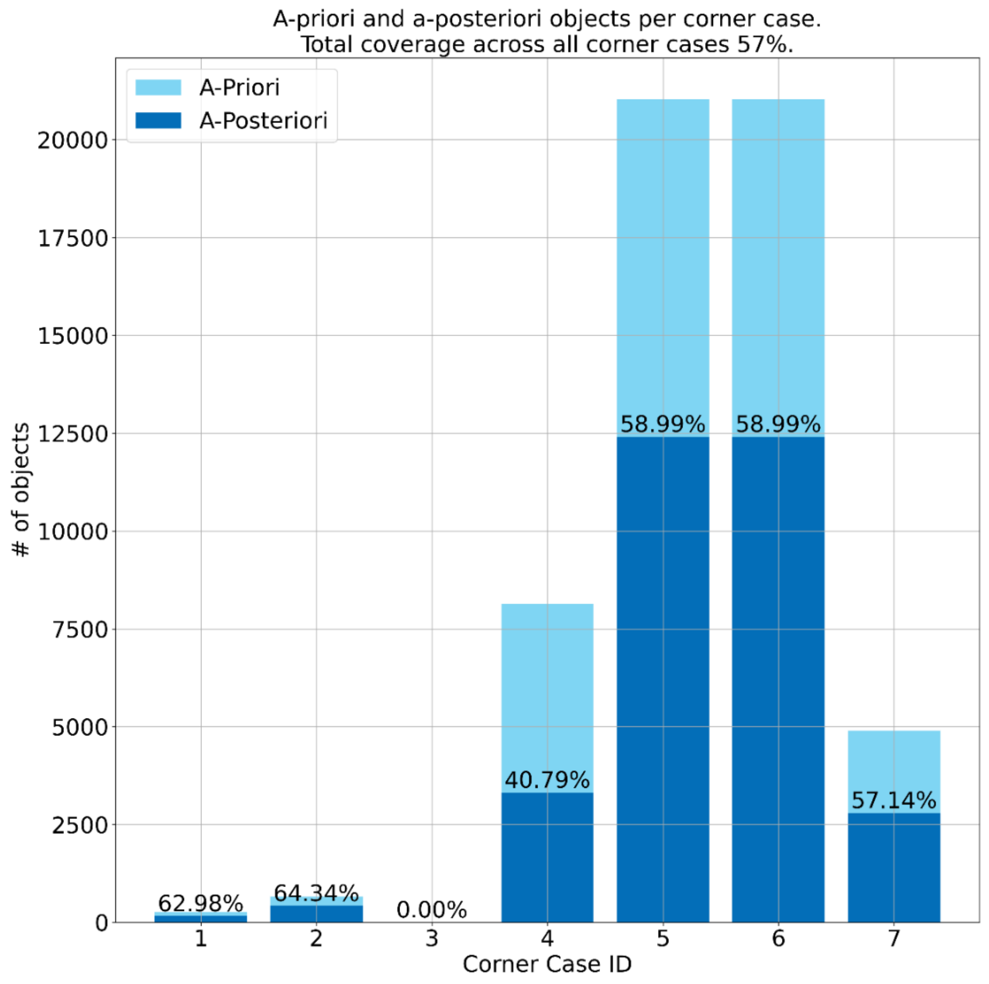
  - Scenes: 83 of total 150 (55%)
- The found corner cases are now analyzed regarding:
  - Layer/Level
  - Each corner case

High level corner case descriptions

1 – Oncoming Traffic at night
2 – High amount of vehicles
3 – Person in wheelchair
4 – Traffic cones on street
5 – Too many reflections (rain)
6 – Attenuation backscattering (rain)
7 – Multipath reflection



5

Corner Case Identification using Cameras and GPS

Corner Case Identification using Cameras and GPS

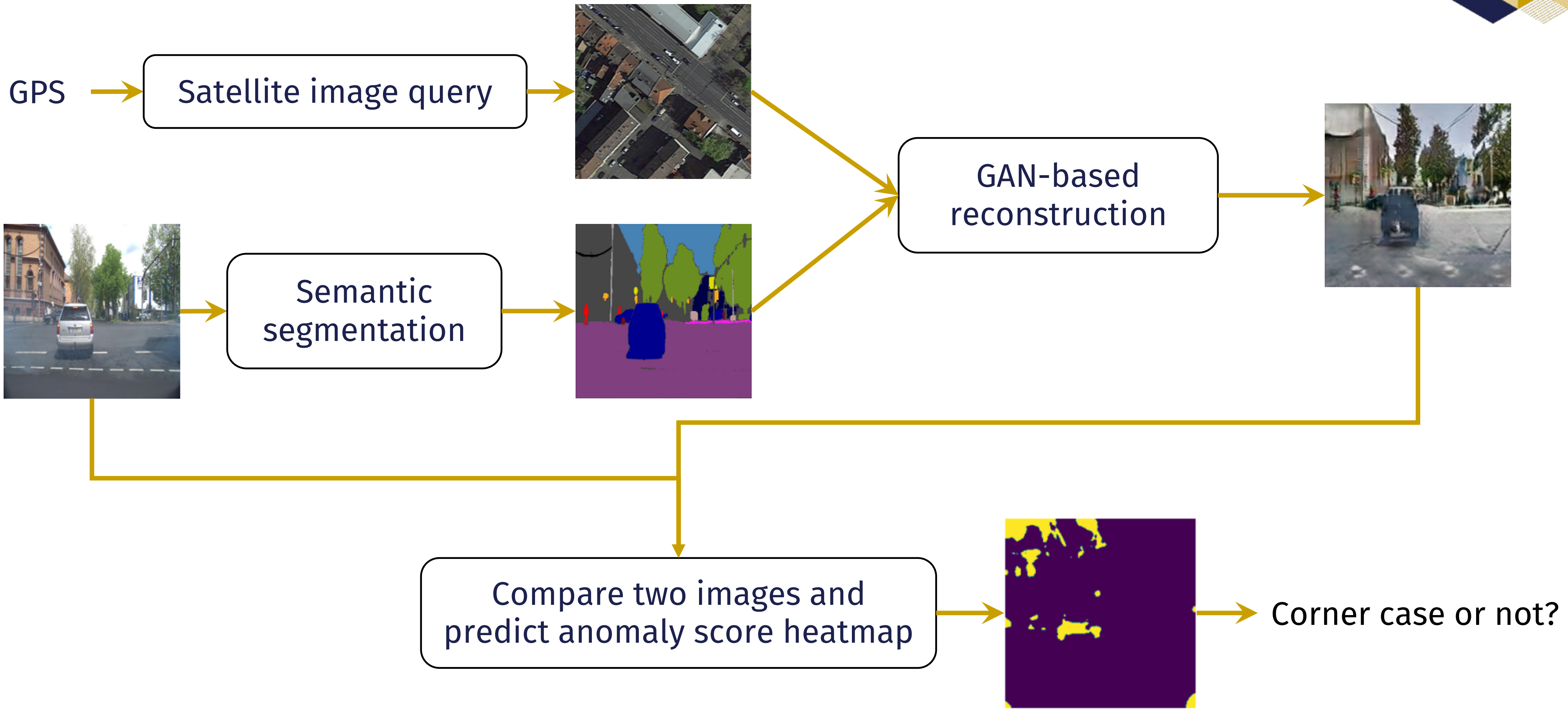
Assumption:

- A target model, when trained on a specific dataset, is expected to effectively fit the majority of data samples.
- The detection of corner case samples is prompted by the target model's underperformance on “unfitted data”.

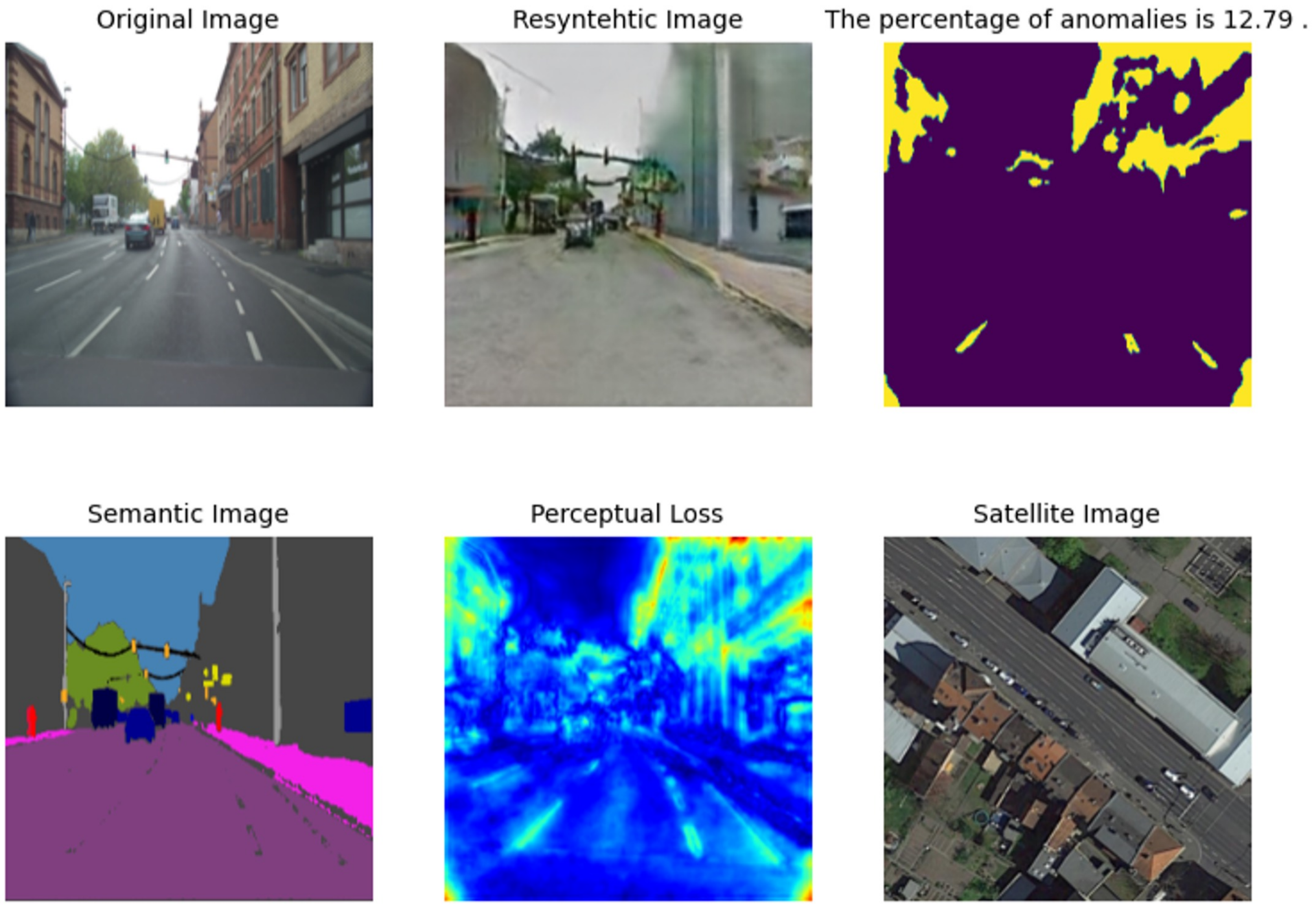
Task-driven corner case identification:

- We select a task with the goal of reconstructing images using bird's-eye-view satellite imagery.
- This task includes the integration of geographic information.
- The choice of the task can be determined on the need for data closed-loop or downstream active learning tasks.

Corner Case Identification using Cameras and GPS

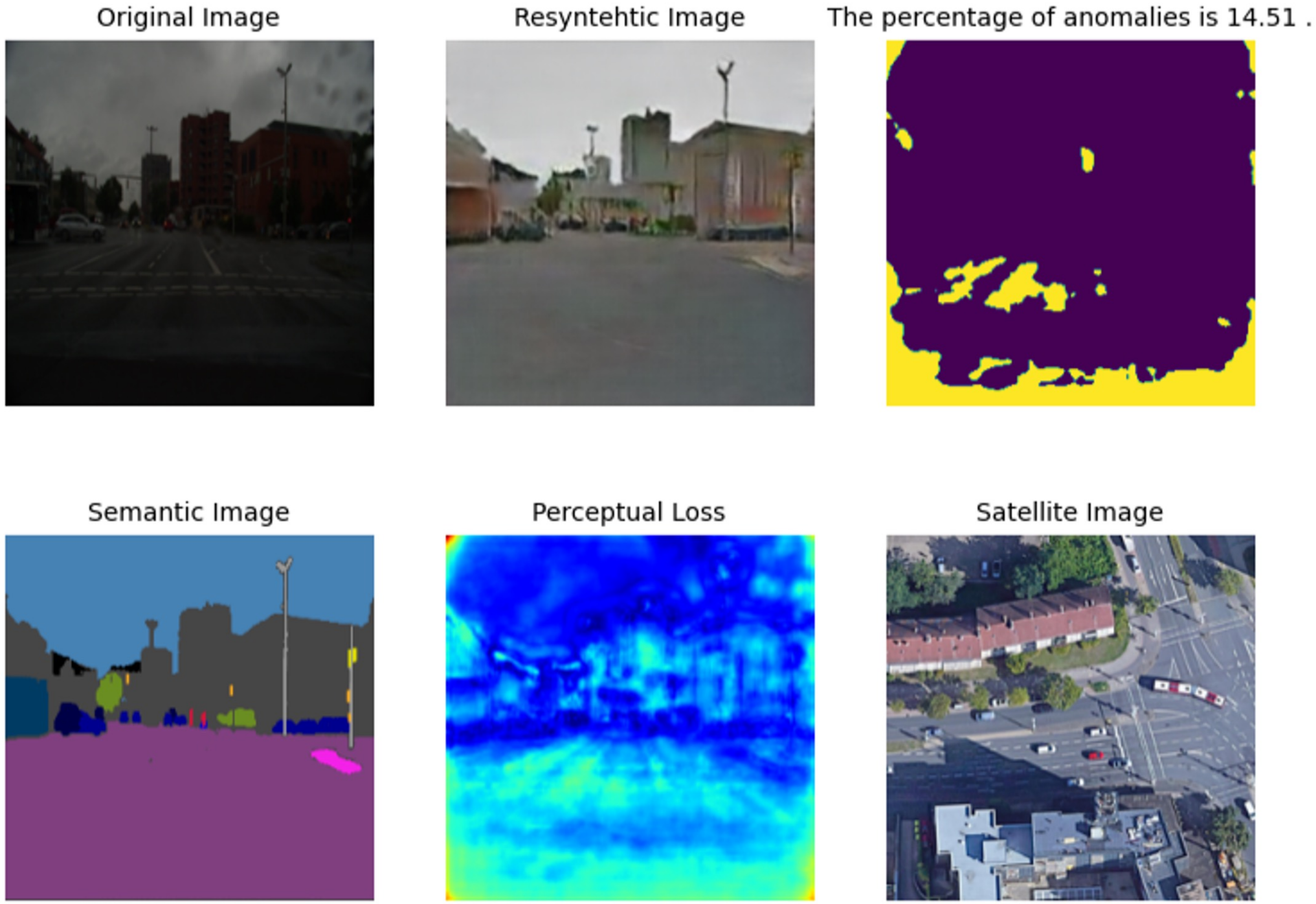


KIDT Example: Building



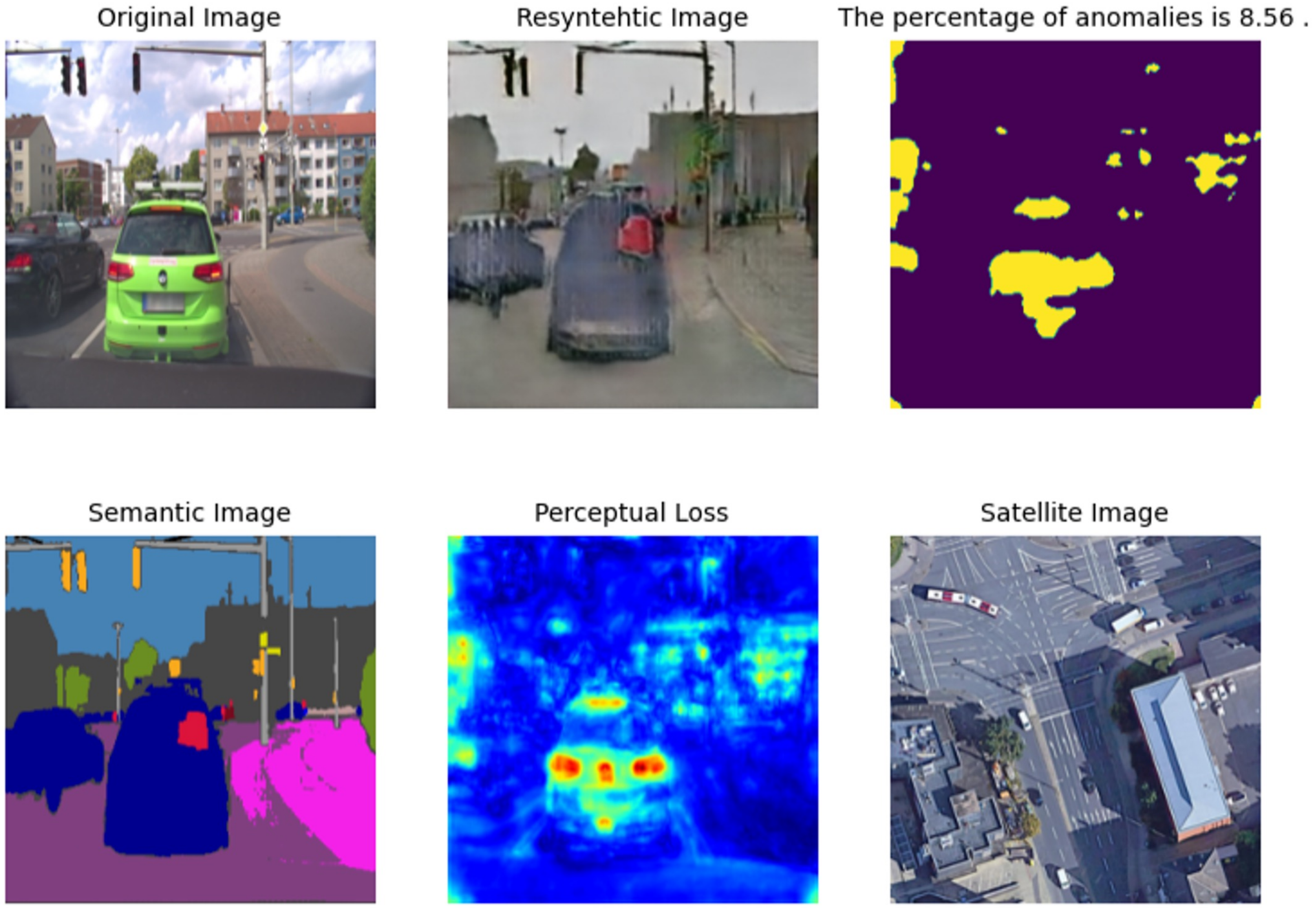
Pretrained dataset for GAN

KIDT Example: Lighting



Pretrained dataset for GAN

KIDT Example: Unexpected Vehicles



Pretrained dataset for GAN

6

Amodal Semantic Segmentation

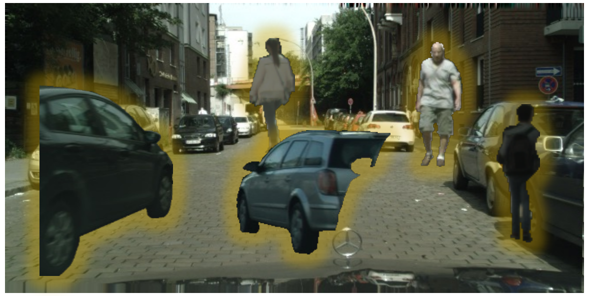
Corner Cases Caused by Occlusions
Motivation to Investigate Amodal Segmentation Methods

- Improved perception performance: amodal segmentation gives a more comprehensive environment understanding
- Enhanced safety: amodal segmentation helps the automated vehicles to recognize (partly) hidden obstacles or pedestrians, reducing the risk of accidents
- More predictable driving: Amodal segmentation can enable vehicles to anticipate movements and intentions of other road users

Problem: Training amodal segmentation methods requires an amodal ground truth

Solution:

On images: copy-paste data augmentation (Amodal Cityscapes) [1]



Paper: Amodal Citiyscapes: A new Dataset, its Generation, and an Amodal Semantic Segmentation Challenge Baseline

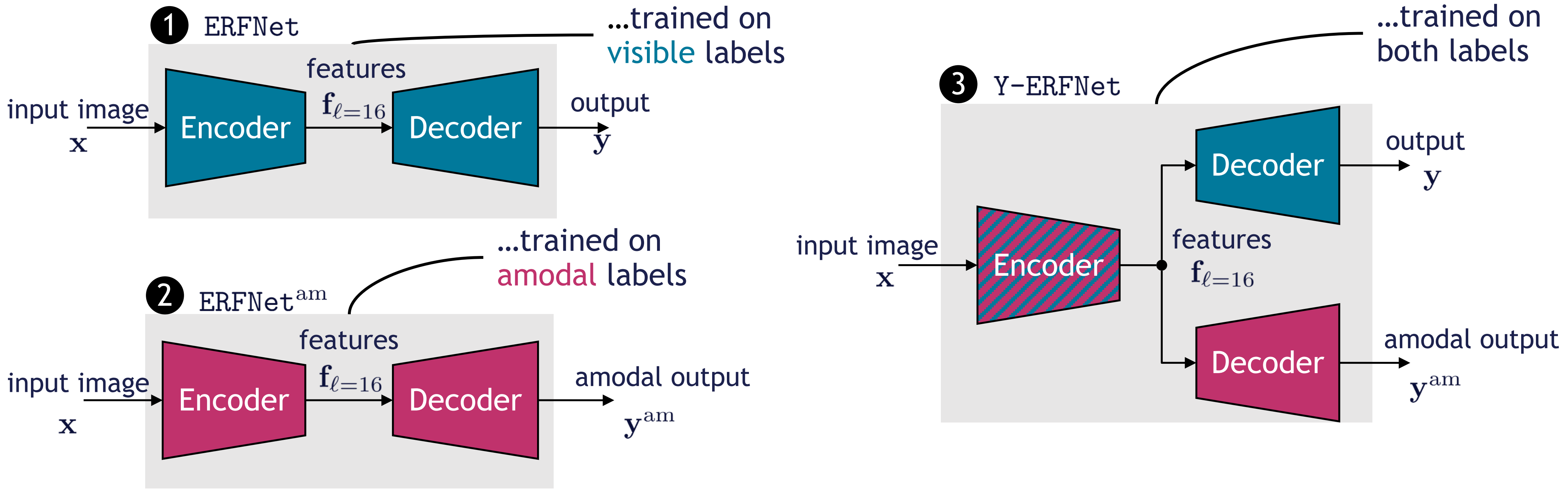
On videos: synthetic data [2]

For our purposes, we split the videos at jump cuts
→ SAIL-VOS-cut

[1] J. Breitenstein, T. Fingscheidt, "Amodal Cityscapes: A New Dataset, its Generation,and an Amodal Semantic Segmentation Challenge Baseline," In Proc. IV, 2022. [2] Y.-T. Hu, H.-S. Chen, K. Hui, J.-B. Huang, A. G. Schwing, "SAIL-VOS: Semantic Amodal Instance Level Video Object Segmentation - A Synthetic Dataset and Baselines," In Proc. CVPR, 2019.

Corner Cases Caused by Occlusions
Amodal Segmentation on Images: Method

Drawback of previous amodal semantic segmentation: classes from the same group cannot occlude each other!
Idea: Train an entirely amodal semantic segmentation predicting all 19 classes separately
Overview of the three investigated methods:



[1] J. Breitenstein, J. Löhdefink, T. Fingscheidt, "Joint Prediction of Amodal and Visible Semantic Segmentation for Automated Driving", In Proc. of ECCV-Workshops, 2022.

Corner Cases Caused by Occlusions
Amodal Segmentation on Images: Evaluation

Poster

Joint Prediction of Visible and Amodal Semantic Segmentation

Results on $\mathcal{D}^{\mathrm{amCS}}_{\mathrm{test}}$ (training on $\mathcal{D}^{\mathrm{amCS}}_{\mathrm{train}}$ for 120 epochs):

Method	Dataset	mIoU	mIoU$^{\mathrm{inv}}$
ERFNet	$\mathcal{D}^{\mathrm{amCS}}_{\mathrm{test}}$	62.99%	5.00%
$\mathrm{ERFNet}^{\mathrm{am}}(K=4)$	$\mathcal{D}^{\mathrm{amCS}}_{\mathrm{test}}$	62.76%	23.60%
$\mathrm{ERFNet}^{\mathrm{am}}$	$\mathcal{D}^{\mathrm{amCS}}_{\mathrm{test}}$	20.16%	36.48%
Y-ERFNet	$\mathcal{D}^{\mathrm{amCS}}_{\mathrm{test}}$	**63.32%**	**43.32%**

groupwise training technique by Purkait et al.[1]

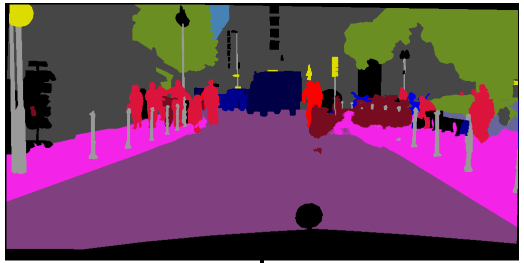
our training technique

Joint visible and amodal segmentation on images outperforms previous works

Qualitative results of Y-ERFNet

$\mathcal{D}^{\mathrm{amCS}}_{\mathrm{test}}$

$\mathcal{D}^{\mathrm{CS}}_{\mathrm{val}}$

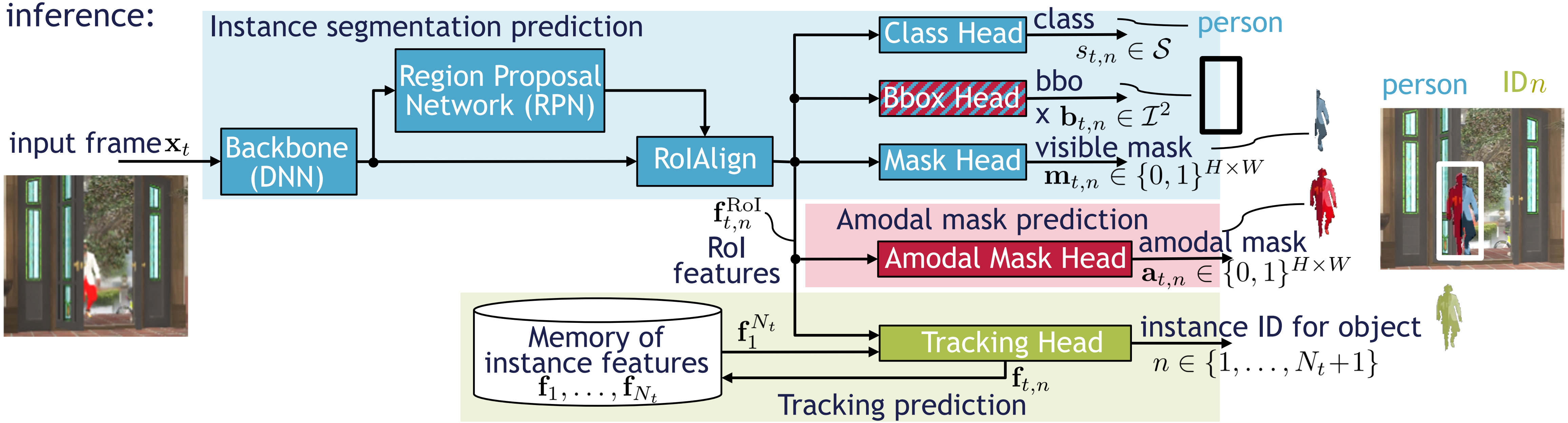


ground truth sem. seg. mask with amodal predictions inserted where instances are pasted

[1] P. Purkait, C. Zach, I. Reid, "Seeing Behind Things: Extending Semantic Segmentation to Occluded Regions", In Proc. of IROS, 2019.
[2] J. Breitenstein, J. Löhdefink, T. Fingscheidt, "Joint Prediction of Amodal and Visible Semantic Segmentation for Automated Driving", In Proc. of ECCV-Workshops, 2022.

Corner Cases Caused by Occlusions
Amodal Segmentation on Videos: Method

Functioning of our proposed VATrack for joint visible and amodal video instance segmentation during inference:



- Simultaneous prediction of amodal and visible instance masks
- Additional tracking of the (amodal) instance masks throughout the sequence
- Instance segmentation prediction is based on Mask R-CNN[2]
- Investigation of two tracking methods: QDTrack (QD)[3] and MaskTrack R-CNN (MT)[4]

[1] J. Breitenstein, K. Jin, A. Hakiri, M. Klingner, T. Fingscheidt, "End-to-End Amodal Video Instance Segmentation", in Proc. of BMVC-Workshops, 2023. [2] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," In Proc. ICCV, 2017. [3] J. Pang, L. Qiu, X. Li, H. Chen, Q. Li, T. Darrell, F. Yu, "Quasi-dense Similarity Learning for Multiple Object Tracking", In Proc. of CVPR, 2021. [4] L. Yang, Y. Fan, N. Xu, „Video Instance Segmentation," In Proc. of ICCV, 2019

Corner Cases Caused by Occlusions
Amodal Segmentation on Videos: Evaluation

- SAIL-VOS-cut splits a video at a jump cut into 2 videos (still same content!)
- Results on SAIL-VOS in the paper

image-based methods

video-based methods

amodal results on image-level (in AP and derivatives) on SAIL-VOS-cut validation data:

Method	DNN	Visible	Amodal	AP	AP_{50}	AP_{50}^{P}	AP_{50}^{H}	AP_{50}^{L}	AP_{50}^{M}	AP_{50}^{S}
MaskAmodal [Hu et al., 2019]	?		✓	13.0	23.0	24.3	16.7	36.6	21.5	6.1
MaskJoint [Hu et al., 2019]	?	✓	✓	14.1	24.8	24.3	<u>18.9</u>	37.8	21.5	5.7
MaskAmodal*	RX101		✓	16.3	25.6	27.4	17.1	35.2	24.2	10.1
MaskJoint*	RX101	✓	✓	16.7	25.6	26.9	17.3	33.0	22.3	9.0
AmodalTrack (MT)	RX101		✓	15.9	25.7	24.9	17.8	36.8	22.8	11.2
Ours: VATrack (MT)	RX101	✓	✓	16.4	26.0	24.9	18.0	**38.6**	22.5	10.6
AmodalTrack (QD)	RX101		✓	<u>17.8</u>	<u>27.4</u>	<u>29.2</u>	18.6	34.7	<u>26.8</u>	<u>11.4</u>
Ours: VATrack (QD)	RX101	✓	✓	**18.3**	**28.6**	**29.7**	**20.1**	<u>38.1</u>	**26.9**	**15.7**

temporal context (TC) can improve results

joint prediction mostly improves image-level results

[1] Y.-T. Hu, H.-S. Chen, K. Hui, J.-B. Huang, A. G. Schwing, "SAIL-VOS: Semantic Amodal Instance Level Video Object Segmentation - A Synthetic Dataset and Baselines," In Proc. CVPR, 2019.
[2] J. Breitenstein, K. Jin, A. Hakiri, M. Klingner, T. Fingscheidt, "End-to-End Amodal Video Instance Segmentation", in Proc. of BMVC-Workshops, 2023.

Corner Cases Caused by Occlusions
Amodal Segmentation on Videos: Evaluation

image-based methods

video-based methods

- SAIL-VOS-cut splits a video at a jump cut into 2 videos (still same content!)
- Results on SAIL-VOS in the paper

amodal results on video-level (in vAP and derivatives) on SAIL-VOS-cut validation data:

Method	DNN	Visible	Amodal	vAP	vAP_{50}	vAP_{50}^{P}	vAP_{50}^{H}	vAP_{50}^{L}	vAP_{50}^{M}	vAP_{50}^{S}
AmodalTrack (MT)	ResNext101		✓	2.4	3.1	3.8	1.7	3.8	1.4	0.4
Ours: VATrack (MT)	ResNext101	✓	✓	2.3	3.1	3.8	1.7	3.7	1.5	0.3
AmodalTrack (QD)	ResNext101		✓	<u>13.1</u>	<u>20.5</u>	<u>21.0</u>	<u>10.7</u>	<u>29.4</u>	<u>14.7</u>	**8.9**
Ours: VATrack (QD)	ResNext101	✓	✓	**14.1**	**22.3**	**22.0**	**12.8**	**32.8**	**15.6**	8.8

MT-based cannot provide meaningful results

joint (QD) prediction mostly improves video-level results

- Video-level metrics also measure the temporal consistency of prediction
  → no evaluation of image-based baselines possible on video level
- Joint prediction of visible and amodal masks can improve results in amodal video instance segmentation
- Temporal context of the video-based methods improves performance
- Results for (visible) video instance segmentation are similar and are in the paper

[1] Y.-T. Hu, H.-S. Chen, K. Hui, J.-B. Huang, A. G. Schwing, "SAIL-VOS: Semantic Amodal Instance Level Video Object Segmentation - A Synthetic Dataset and Baselines," In Proc. CVPR, 2019.
[2] J. Breitenstein, K. Jin, A. Hakiri, M. Klingner, T. Fingscheidt, "End-to-End Amodal Video Instance Segmentation", in Proc. of BMVC-Workshops, 2023.

Corner Cases Caused by Occlusions

Amodal Segmentation on Videos: Evaluation

Poster Video Amodal Segmentation and Challenge

7

Relevance Estimation of Corner Cases

Relevance Estimation of Corner Cases for Semantic Segmentation
Motivation

- We know definitions for knowledge-driven corner cases from before [Heidecker et al., 2021]

Problem:

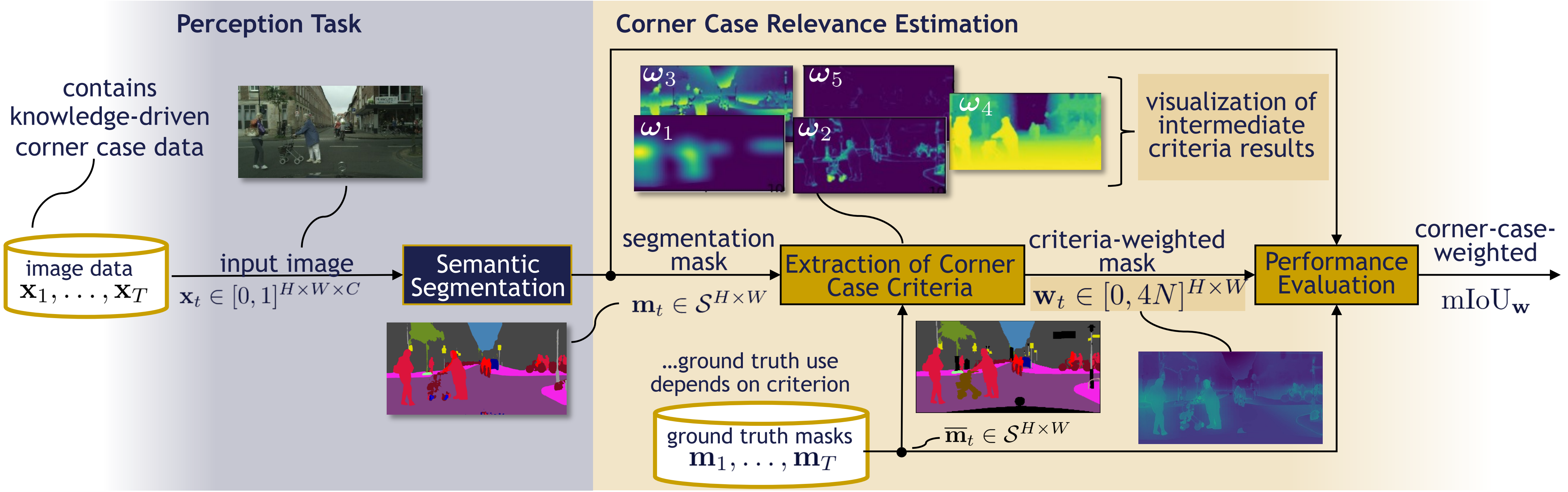
- We don't know which type of corner case affects a perception method in which way
- Typical metrics for quality of a perception method are task-agnostic

Solution:

- Corner-case-weighted mIoU based on pixel-wise weightings to measure the effect of corner cases on the performance in semantic segmentations
- Pixel-wise weightings are obtained from simple corner case criteria

[1] F. Heidecker, J. Breitenstein, K. Rösch, J. Löhdefink, M. Bieshaar, C. Stiller, T. Fingscheidt, B. Sick: "An Application-Driven Conceptualization of Corner Cases for Perception in Highly Automated Driving", Proc. of IV, 2021.

Relevance Estimation of Corner Cases for Semantic Segmentation Pipeline



Weighted intersection over union: $\mathrm{IoU}_{\mathbf{w}}(s) = \frac{\sum_{i \in \mathcal{I}} \mathrm{TP}(i,s)}{\sum_{i \in \mathcal{I}} \mathrm{TP}(i,s) + (\mathrm{FP}(i,s) + \mathrm{FN}(i,s)) \cdot w(i)}$

Aggregated pixel-wise weights: $w(i) = \frac{1}{N} \sum_{n \in \mathcal{N}} \lambda_n \omega_n(i)$ $\mathbf{w}_t$

corner case criteria weights

Poster

Corner Case Generation and Detection Approaches

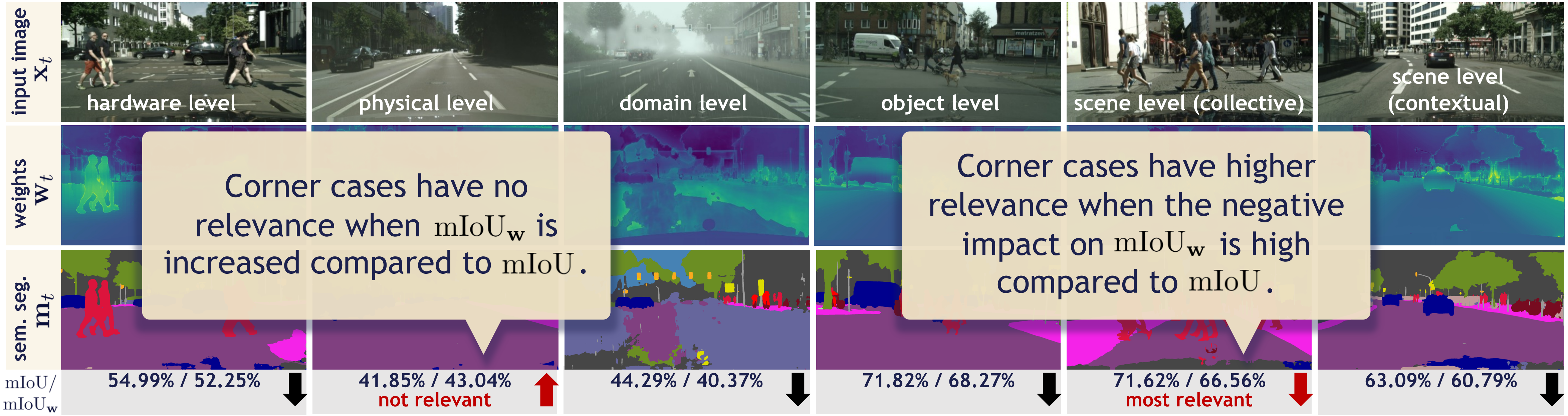
Relevance Estimation of Corner Cases for Semantic Segmentation Evaluation of Relevance Estimation

Evaluation on Cityscapes dataset and a dataset of pre-selected corner cases for OCRNet

	$\mathcal{D}_{\mathrm{CS}}^{\mathrm{val}}$	$\mathcal{D}_{\mathrm{CS}}^{\mathrm{CC}}$
mIoU	80.23%	74.12%
$\mathrm{mIoU}_{\mathbf{w}}$	80.35%	72.33%

Similar values on “normal” dataset $\mathcal{D}_{\mathrm{CS}}^{\mathrm{val}}$ **but decrease** in $\mathrm{mIoU}_{\mathbf{w}}$ on the corner case dataset $\mathcal{D}_{\mathrm{CS}}^{\mathrm{CC}}$

mIoU and $\mathrm{mIoU}_{\mathbf{w}}$ for example images of corner case types $\mathbf{x}_t$ with weights $\mathbf{w}_t$ and corresponding segmentation masks $\mathbf{m}_t$:



Summary:
Relevance Estimation of Corner Cases for Semantic Segmentation

- Introduction of **relevance-adapted** version of mIoU to adapt to the task of corner case identification
- For OCRNet collective anomalies and domain-level corner cases have the highest relevance
- Physical-level corner cases have no relevance for OCRNet
- The novel $\mathrm{mIoU}_{\mathbf{w}}$ establishes a **link between corner case types and perception method**

We can use $\mathrm{mIoU}_{\mathrm{w}}$ to estimate the relevance of corner cases for a semantic segmentation method

This work is a collaboration of partners in AP2.3: TU BS, Uni Kassel, Bosch, FZI

Paper: What does Really Count? Estimating Relevance of Corner Cases: For Semantic Segmentation in Automated Driving

Poster

Relevance Estimation of Corner Cases for Semantic Segmentation

8

Driving with the Eyes of AI

Driving with the Eyes of AI

- Experimental setup that allows to control a vehicle based on the prediction of a real-time semantic segmentation network
- Use of human risk perception to find safety-critical driving situations

- Two publications have been published using this experimental setup:
  - K. Kowol., S. Bracke., and H. Gottschalk., **A-Eye: Driving with the Eyes of AI for Corner Case Generation**, in Proceedings of the 6th International Conference on Computer-Human Interaction Research and Applications - CHIRA, INSTICC, SciTePress, 2022, pp. 41
  - K. Kowol, S. Bracke, and H. Gottschalk, **survAIval: Survival Analysis with the Eyes of AI**, in Computer-Human Interaction Research and Applications, A. Holzinger, H. P. da Silva, J. Vanderdonckt, and L. Constantine, eds., Cham, 2023, Springer Nature Switzerland, pp. 153–170

A-Eye - Approach

safety-critical driving situation

fast + safe

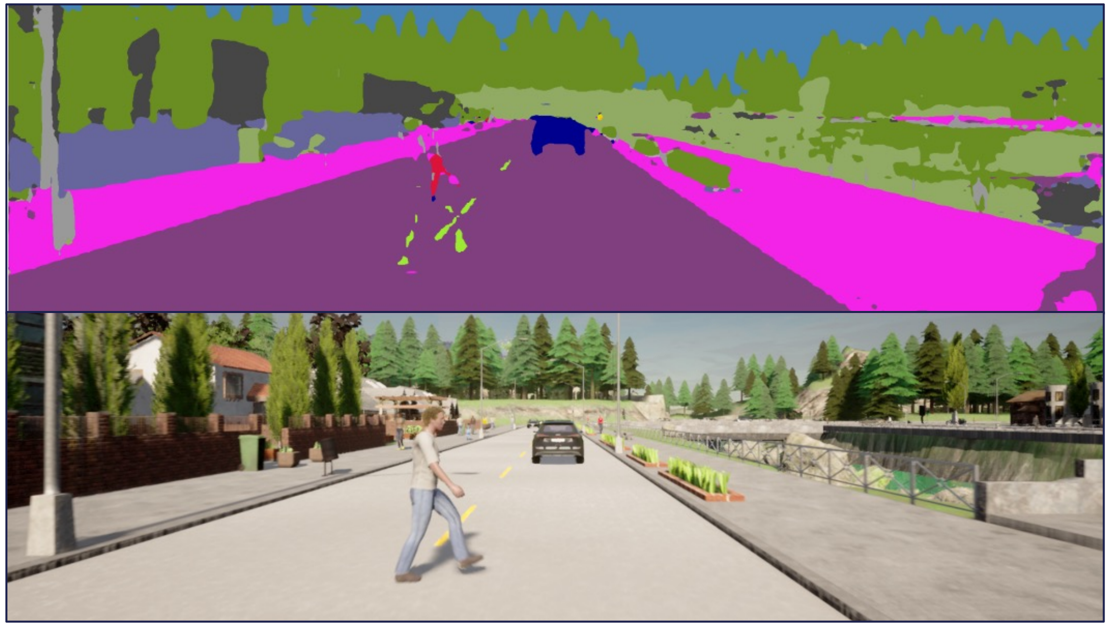
CC	HITL	simulation

semantic segmentation

driving simulator

A-Eye - Driving Simulator

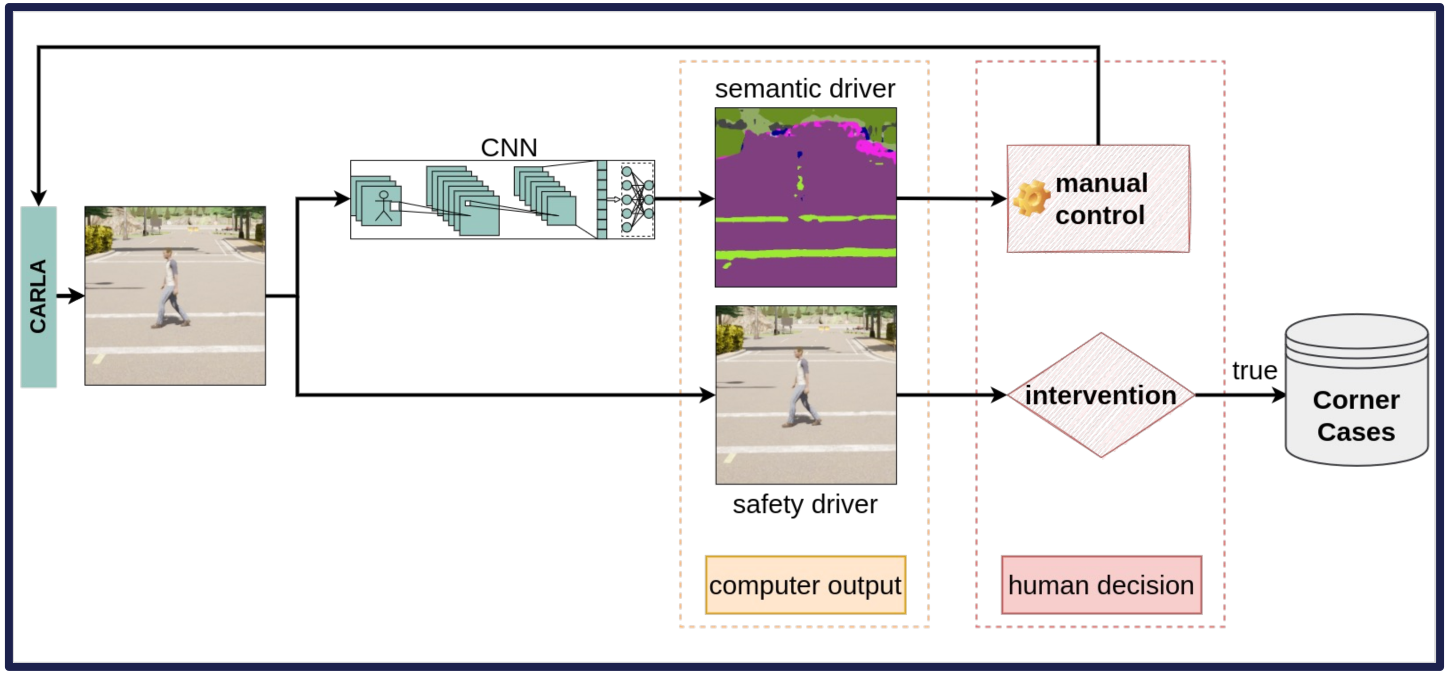
Driving simulator including steering wheels, pedals, seats and screens.



View of the semantic driver (top) and the safety driver (bottom).

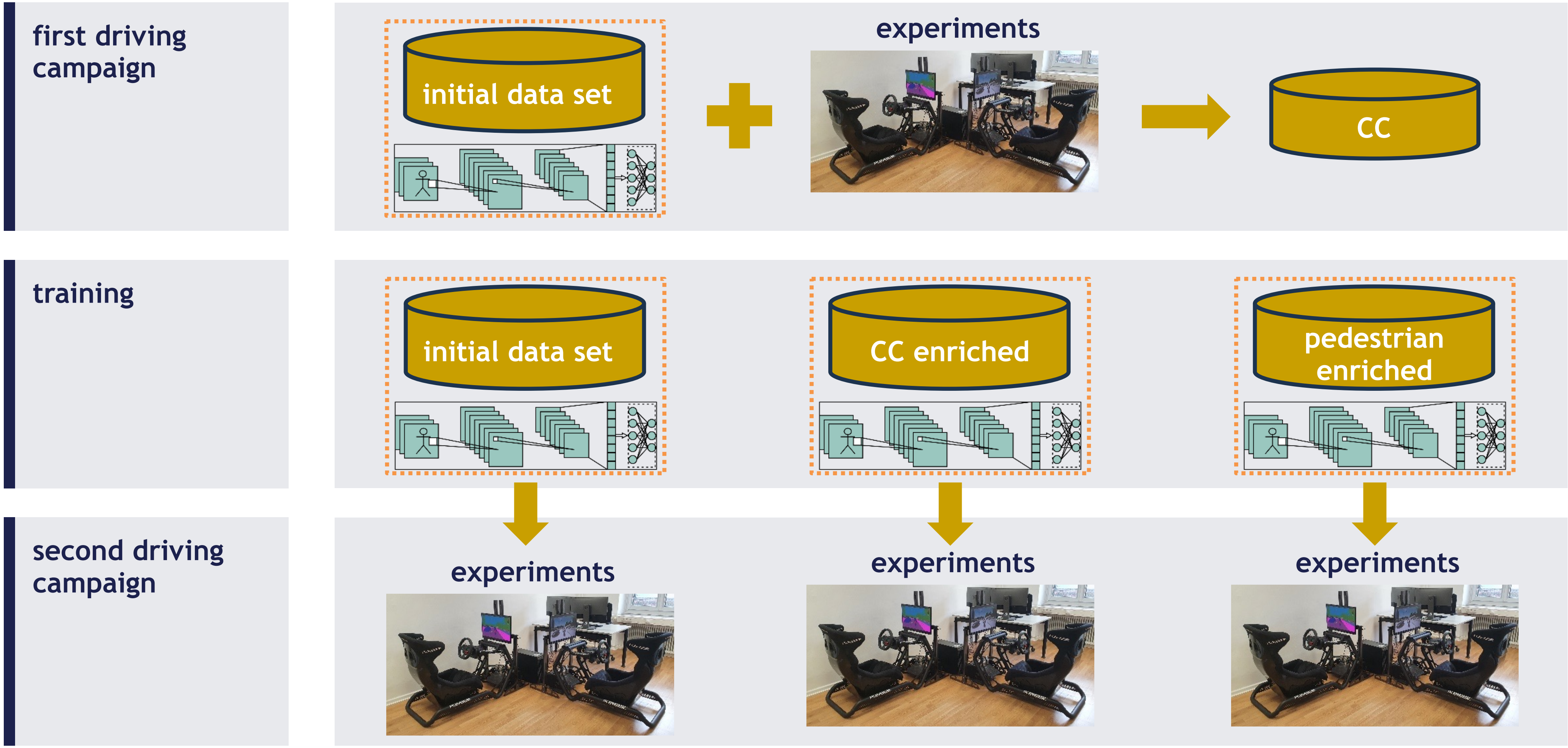
A-Eye – Corner Case Retrieval

- Two student drivers (free driving)
- Segmentation network: Fast-SCNN† (not fully trained)



† Rudra P. K. Poudel, Stephan Liwicki, and Roberto Cipolla. “Fast-SCNN: Fast Semantic Segmentation Network”. In: 30th British Machine Vision Conference 2019, BMVC 2019, Cardiff, UK, September 9-12, 2019. BMVA Press, 2019, p. 289.

A-Eye - Experiments



A-Eye - Results

- Drivers had no idea what kind of network they were driving with.

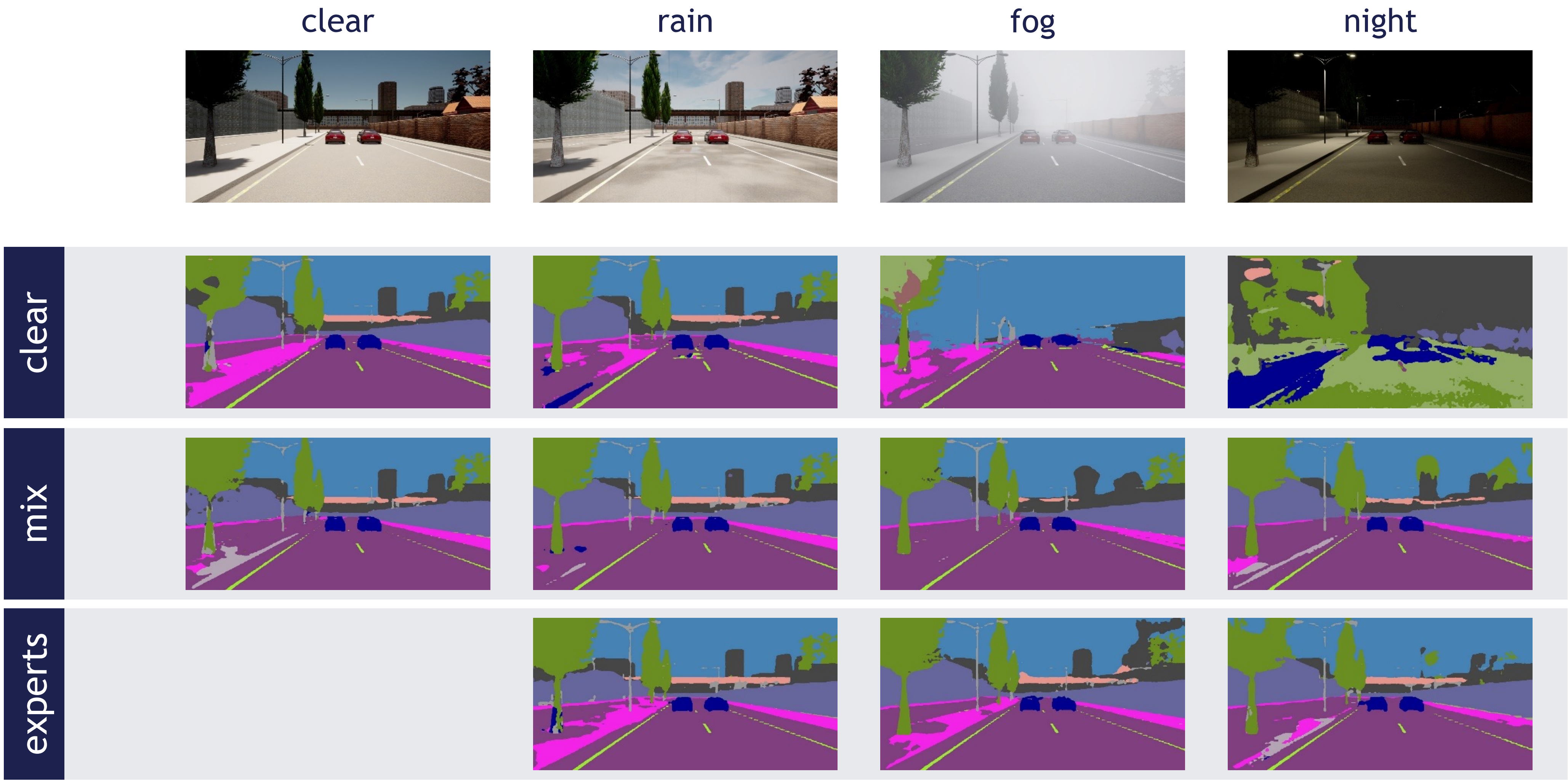
dataset	d	t	# CC	$\bar{d}$	s_d	$\bar{t}$	s_t
	[km]	*[min]*	*[-]*	*[km/CC]*	*[km/CC]*	*[min/CC]*	*[min/CC]*
initial dataset	121.32	411	13	7.73	14.25	25.93	39.60
pedestrian enriched	163.09	500	21	7.52	10.47	23.25	28.72
corner case enriched	153.38	528	11	**13.84**	8.68	**47.47**	31.87

- Safety-critical corner cases recorded by intentional perceptional distortions improves the performance!

survAIval - Survival Analysis with the Eyes of AI

- **Idea:** reduce development time and use models trained on standard data
- Investigation of expert models vs. universal model using survival analysis
- Experimental approach:
  - 4 environmental conditions
  - 3 Model types:
    - baseline
    - expert for night, fog or rain
    - Universal
  - CC means leaving the study

survAIval - Model Performance on Environmental Conditions



survAIval - Survival Analysis with the Eyes of AI

- Experiments similar to A-Eye but with 10-minute drives
- A total of 160 drives, 48 corner cases detected

model	training	test			
		clear	rain	fog	night
baseline	clear	4	5	13	17
experts	rain	-	0	-	-
	fog	-	-	0	-
	night	-	-	-	1
universal	mix	1	3	1	3

survAIval - Kaplan-Meier-Estimator

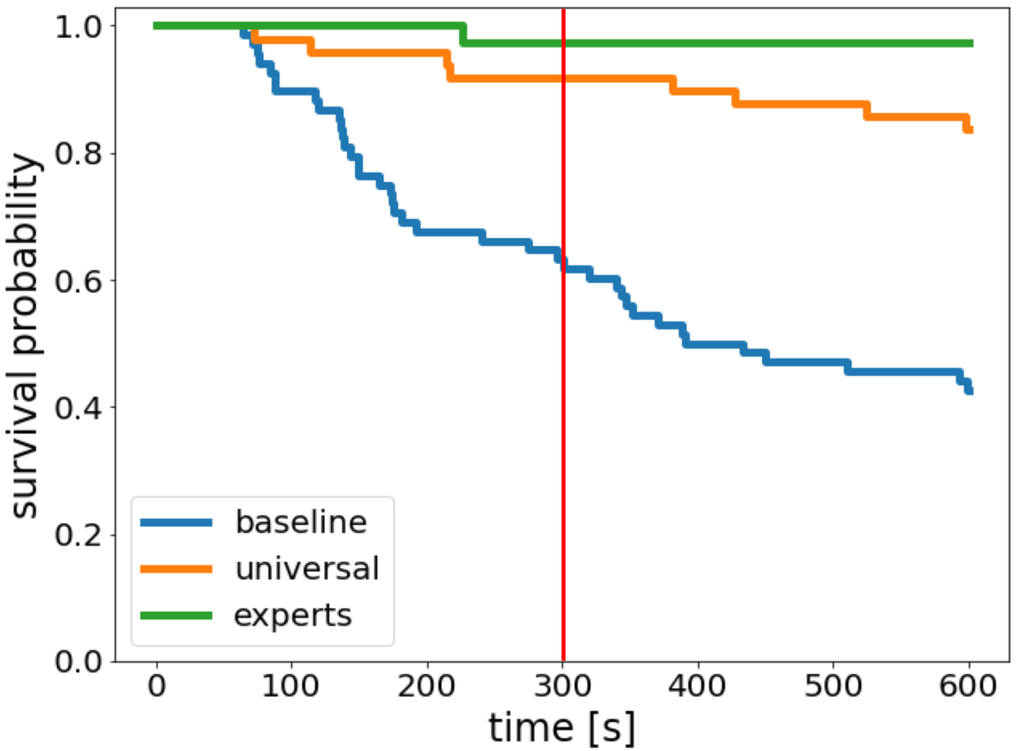
- Statement of how likely it is that a corner case will not occur in the considered time interval
- No statement about the individual factors

$$S(t_j) = \prod_{i=0}^{j} \frac{n_i - d_i}{n_i}$$

j: number of time intervals

n: number of entities still alive at time Δt

d: number of entities leaving the study



survAIval - Cox Proportional Hazards Model

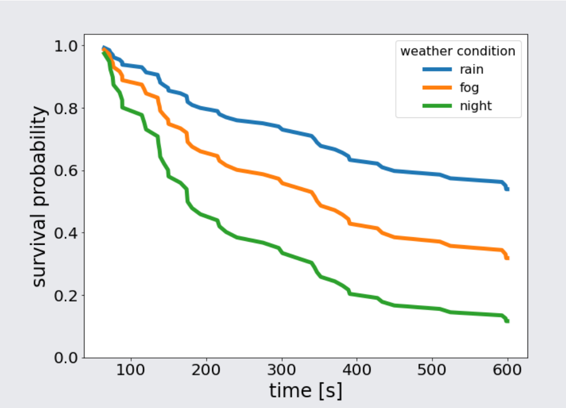
- Survival time estimation considering various influencing variables

$$h(t,\mathbf{Z}) = h_0(t)\exp\left(\sum_{i=1}^{p}\beta_i Z_i\right), \quad \mathbf{Z} = \overbrace{(Z_1, Z_2, \ldots, Z_p)}^{\boxed{\text{rain, fog, night}}}$$

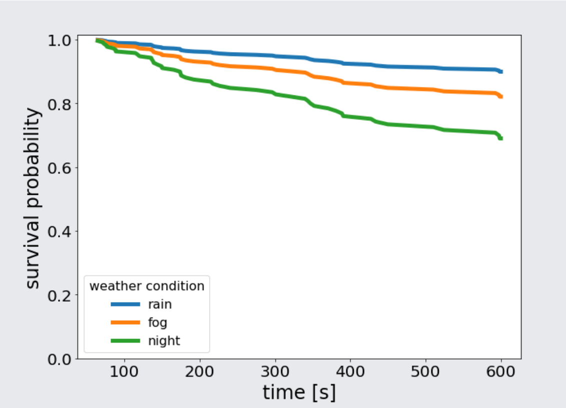
h_0: baseline hazard

Z: time-independent influencing variables

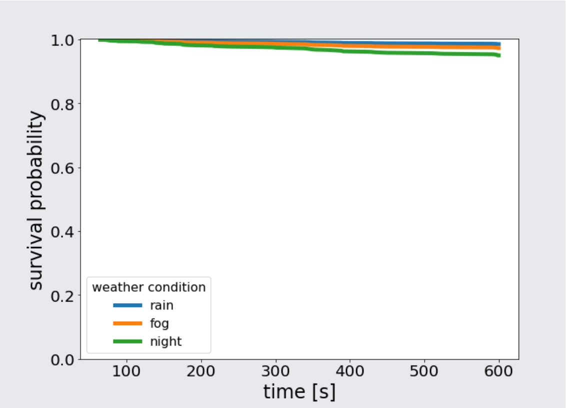
β: regression coefficients



baseline



universal



experts

- It seems to be useful to focus on some basic data and add other models for special cases

Corner Case Publication List

Heidecker et al., „Towards Corner Case Detection by Modeling the Uncertainty of Instance Segmentation Networks”, In Proc. of ICPR, IADS Workshop, 2019

Möller et al., “ Out-of-distribution Detection and Generation using Soft Brownian Offset Sampling and Autoencoders”, In Proc. of CVPR, SAIAD Workshop, 2021

Heidecker et al., “An Application-Driven Conceptualization of Corner Cases for Perception in Highly Automated Driving”, In Proc. of the IV, 2021.

Bogdoll et al., “Description of Corner Cases in Automated Driving: Goals and Challenges”, In Proc. of ICCV, ERCVAD Workshop, 2021.

Heidecker et al, “Detecting Corner Case in the Context of Highly Automated Driving”, In OCDDC, 2021.

Rösch et al, “Space, Time, and Interaction: A Taxonomy of Corner Cases in Trajectory Datasets for Automated Driving”, In Proc. of SSCI, IEEE CIVTS, 2022.

Breitenstein et al., “Amodal Cityscapes: A New Dataset, its Generation, and an Amodal Semantic Segmentation Challenge Baseline”, In Proc. IV, 2022.

Bogdoll et al., “Anomaly Detection in Autonomous Driving: A Survey”, In Proc. of CVPR Workshops, 2022.

Heidecker et al., “Sampling-based Uncertainty Estimation for an Instance Segmentation Network”, arXiv preprint arXiv:2305.14977, 2023.

Bogdoll et al., “One Ontology to Rule Them All: Corner Case Scenarios for Autonomous Driving”, In Proc. of ECCV-Workshops, 2022.

Kowol et al., “A-Eye: Driving with the Eyes of AI for Corner Case Generation”, In Proc. of CHIRA, 2022.

Maag et al., “Two Video Data Sets for Tracking and Retrieval of Out of Distribution Objects”, In Proc. of ACCV, 2022.

Breitenstein et al., “Joint Prediction of Amodal and Visible Semantic Segmentation for Automated Driving”, In Proc. of ECCV-Workshops, 2022.

Bogdoll et al., “Perception Datasets for Anomaly Detection in Autonomous Driving: A Survey”, In Proc. of IV, 2023.

Kowol et al., “survAIval: Survival Analysis with the Eyes of AI”, In Computer-Human Interaction Research and Applications, 2023.

Tülleners et al., “A Semi-Automated Corner Case Detection and Evaluation Pipeline”, arXiv preprint arXiv:2305.16369, 2023.

Heidecker et al., “Context Information for Corner Case Detection in Highly Automated Driving”, In Proc. of ITSC, 2023.

Heidecker et al., “Corner Case Definition in Machine Learning Processes”, In AI Perspectives & Advances, 2023.(Accepted)

Bogdoll et al., “Conditioning Latent-Space Clusters for Real-World Anomaly Classification”, In Proc. of SSCI, 2023. (Accepted)

Breitenstein et al., “What Does Really Count? Estimating Relevance of Corner Cases for Semantic Segmentation in Automated Driving”, In Proc. of ICCV Workshops, 2023.

Heidecker et al., “Criteria for Uncertainty-based Corner Cases Detection in Instance Segmentation”, (Review)

Breitenstein et al., “End-to-end Amodal Video Instance Segmentation”, In Proc. of BMVC Workshop, 2023.

Questions

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KI Data Tooling is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

www.ki-datatooling.de @KI_Familie KI Familie

KI DATA TOOLING
The Data Kit for Automotive AI

KI FAMILIE

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Federal Ministry for Economic Affairs and Climate Action

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