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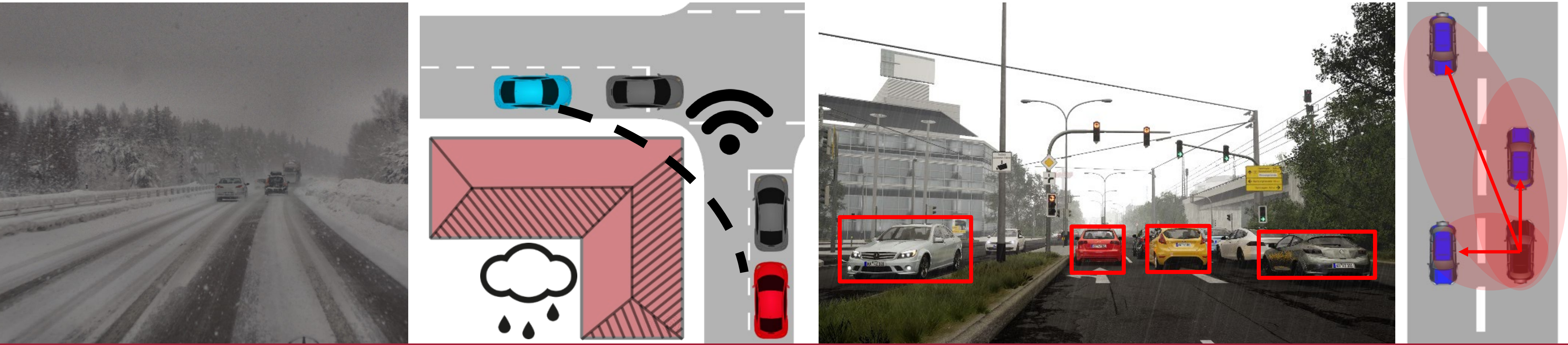


Robust Local and Collective Perception under Varying Weather Conditions

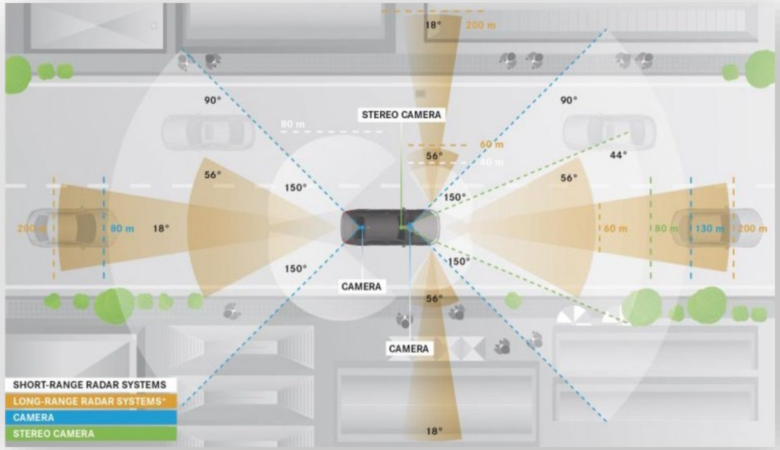
04.09.2023 | Georg Volk

Motivation

21% of all accidents in the United States are weather-related

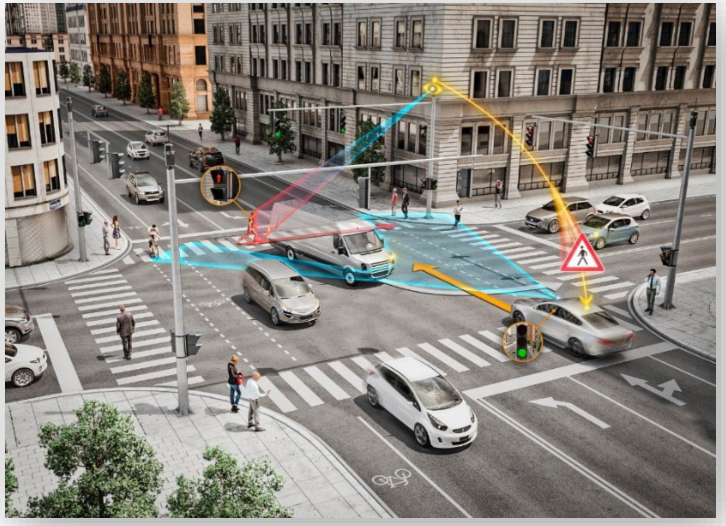
Source: NHTSA, https://ops.fhwa.dot.gov/weather/q1_roadimpact.htm

Various local sensors



Source:: Daimler AG, Daimler Intelligent Drive

Collective perception can deal with obstructions



Source: Continental AG

Environmental influences affect sensors!

Source: pxhere.com

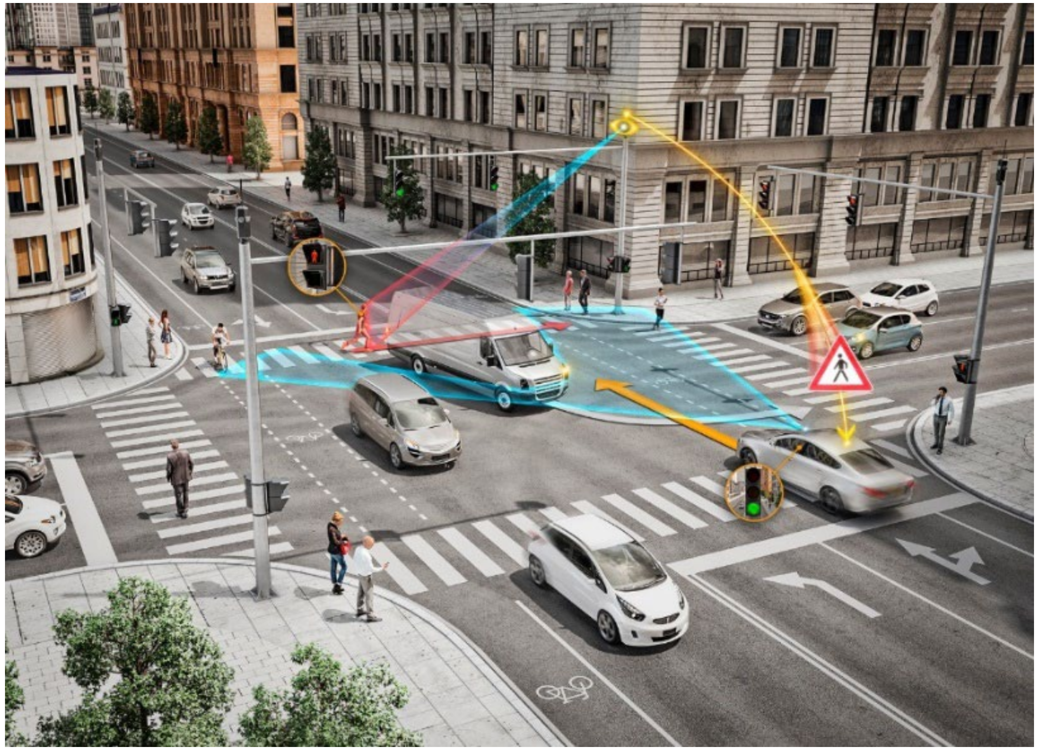
Motivation

- Collective perception increases test complexity

- Large scale simulations with focus on communication

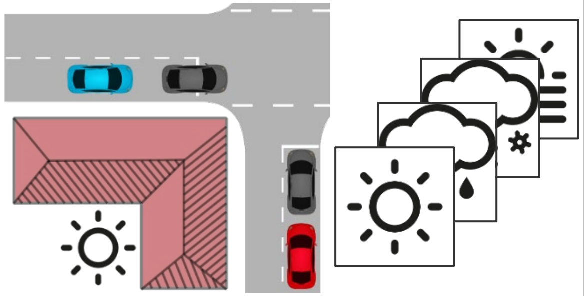
Source: https://www.eclipse.org/sumo   Source: https://github.com/riebl/artery

- Mostly idealistic or probabilistic perception considered



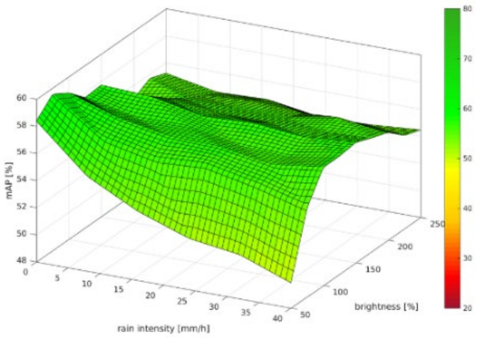
Source: Continental AG

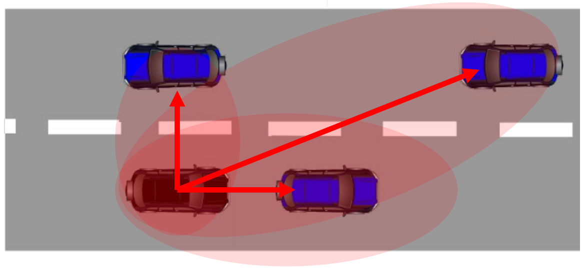
→ Realistic perception pipeline for robust perception!



Simulation – Perception Pipeline

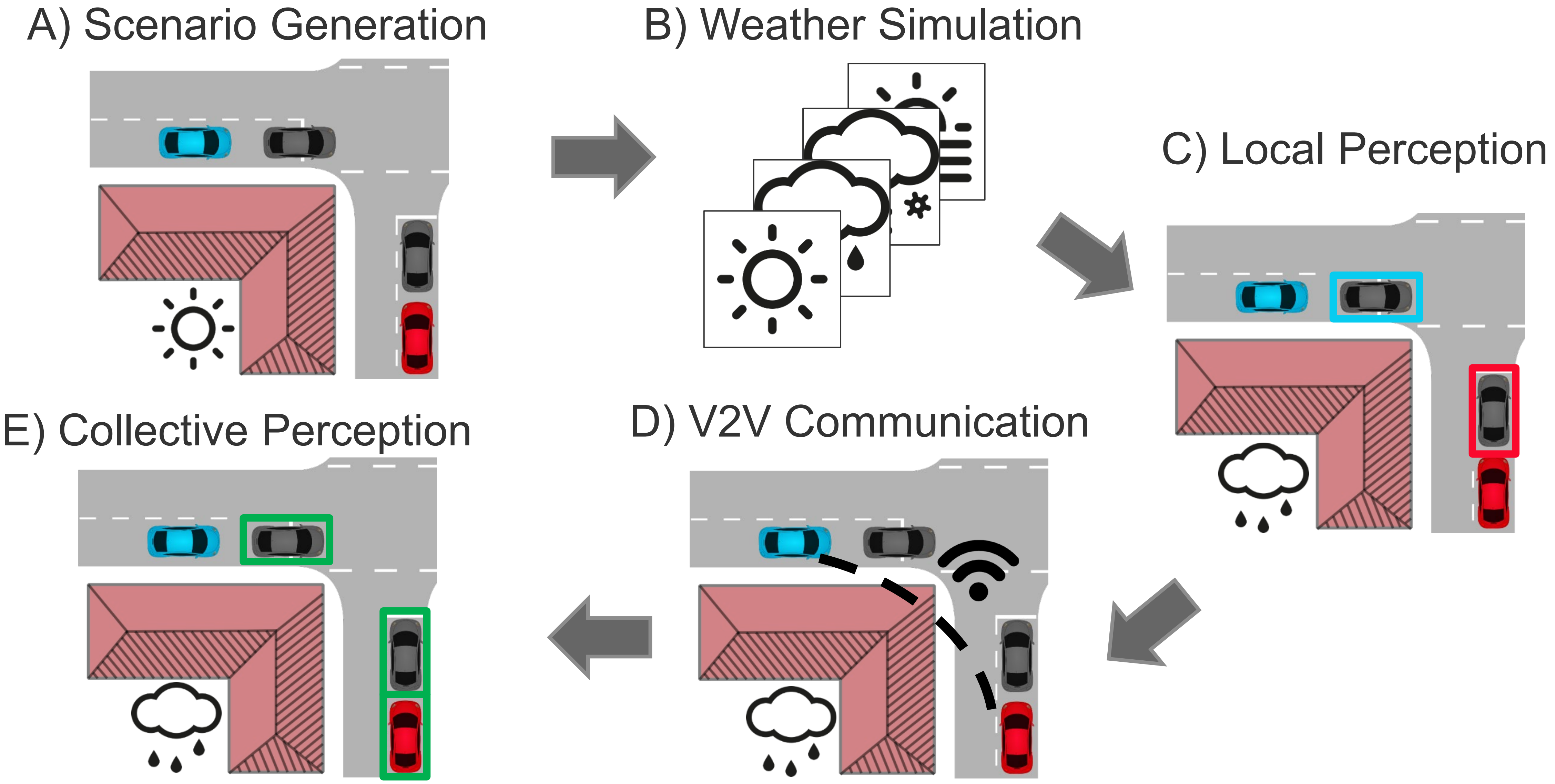
Optimization – Local & Collective



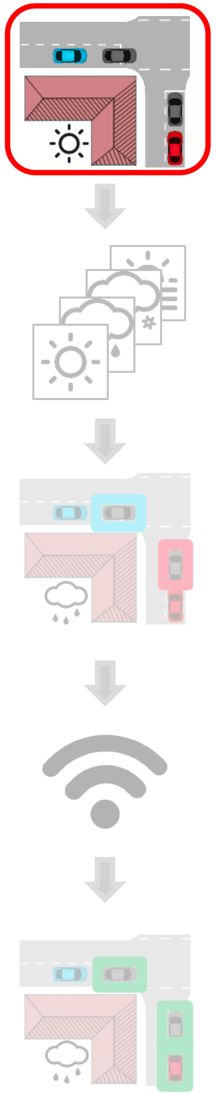


Evaluation – Safety Metric

Environment-aware Collective Perception Pipeline

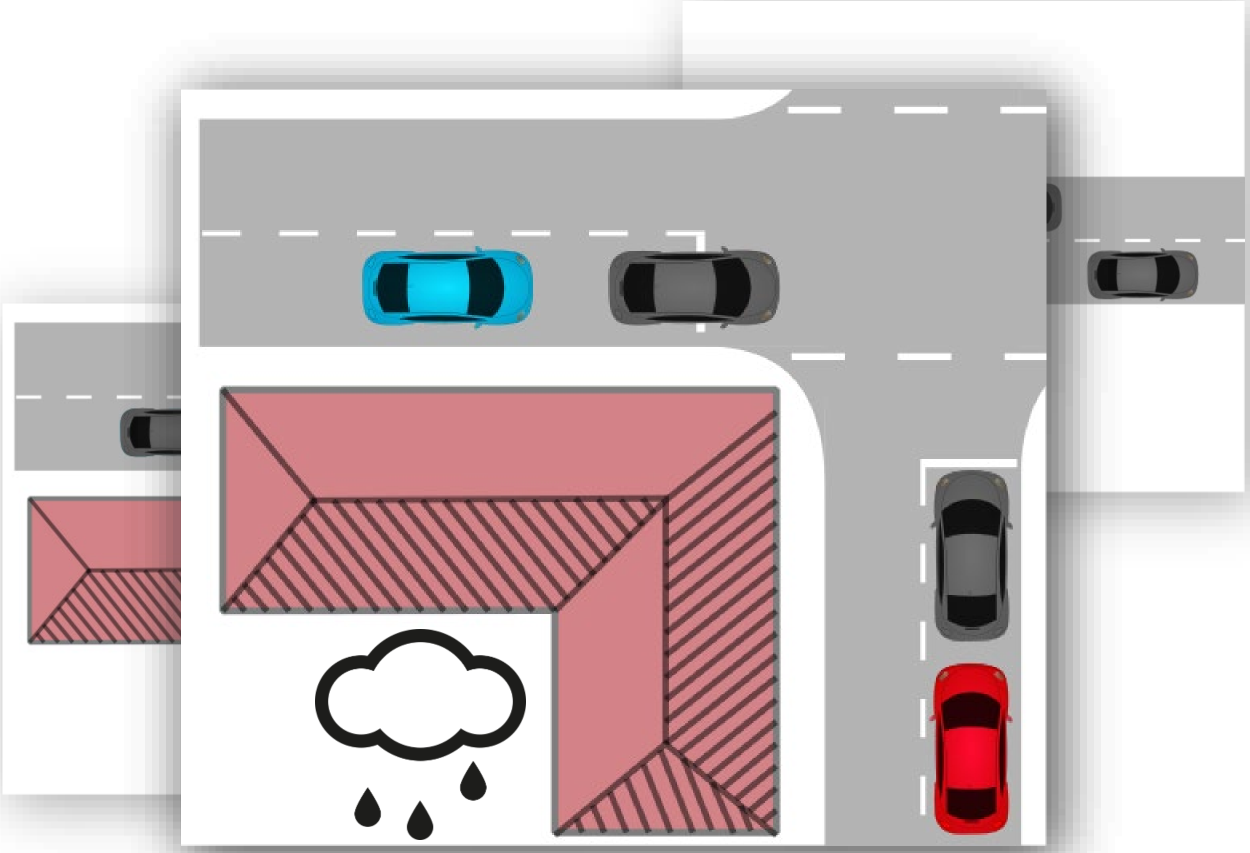


A) Scenario Generation

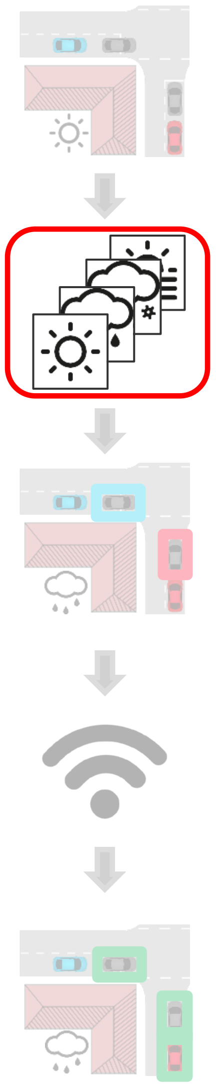


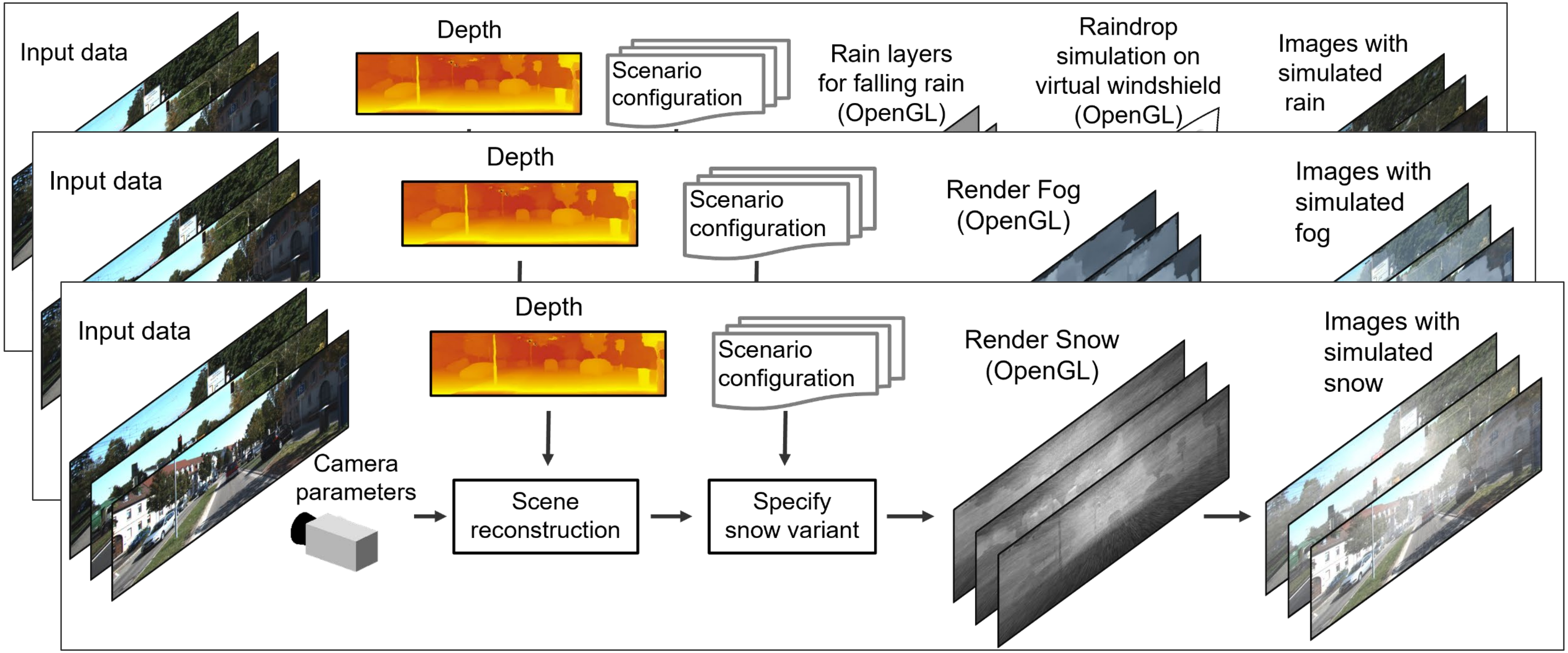
- Use Carla as simulator
- Choose map
- Specify cooperative vehicles
- Specify ego vehicle
- Configure weather variant

→Simulation will be automatically configured according to settings



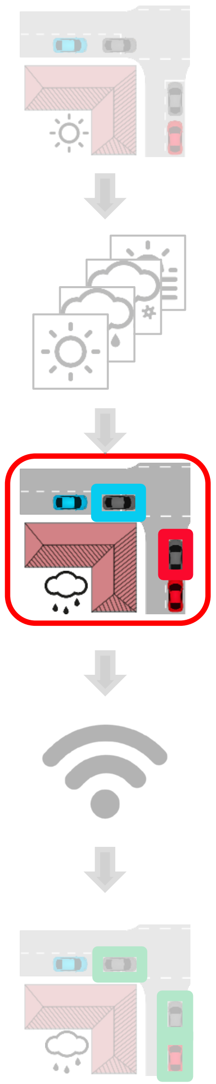
B) Weather Simulation



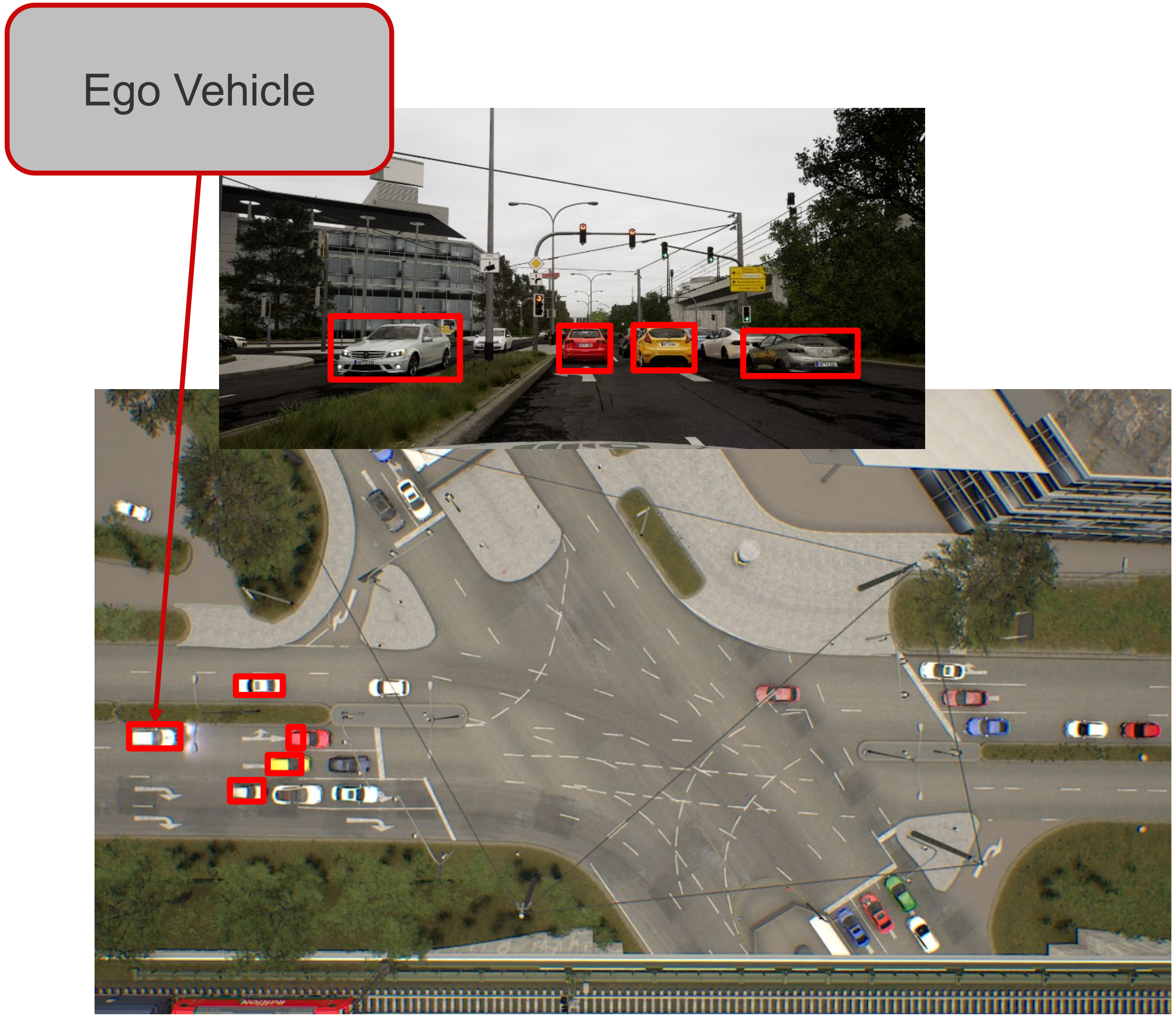


Snow Simulation

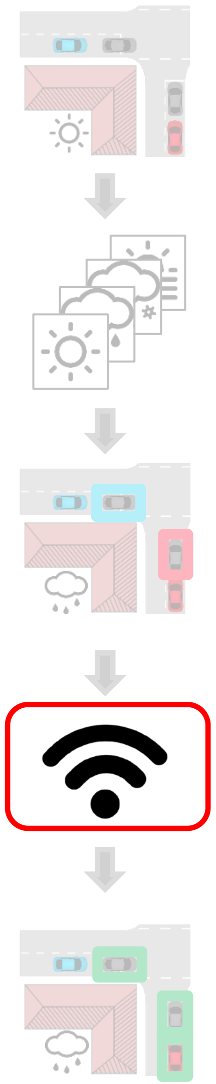
C) Local Perception



- Object detection with
  - Faster R-CNN, YOLO
- Estimation of 3D position with depth map
- Local tracking
  - KF, EKF or UKF
  - Object association
    - Nearest Neighbors
    - Hungarian Algorithm
  - Movement models:
    - CV, CA, CTRA
- Consider processing delay in simulation

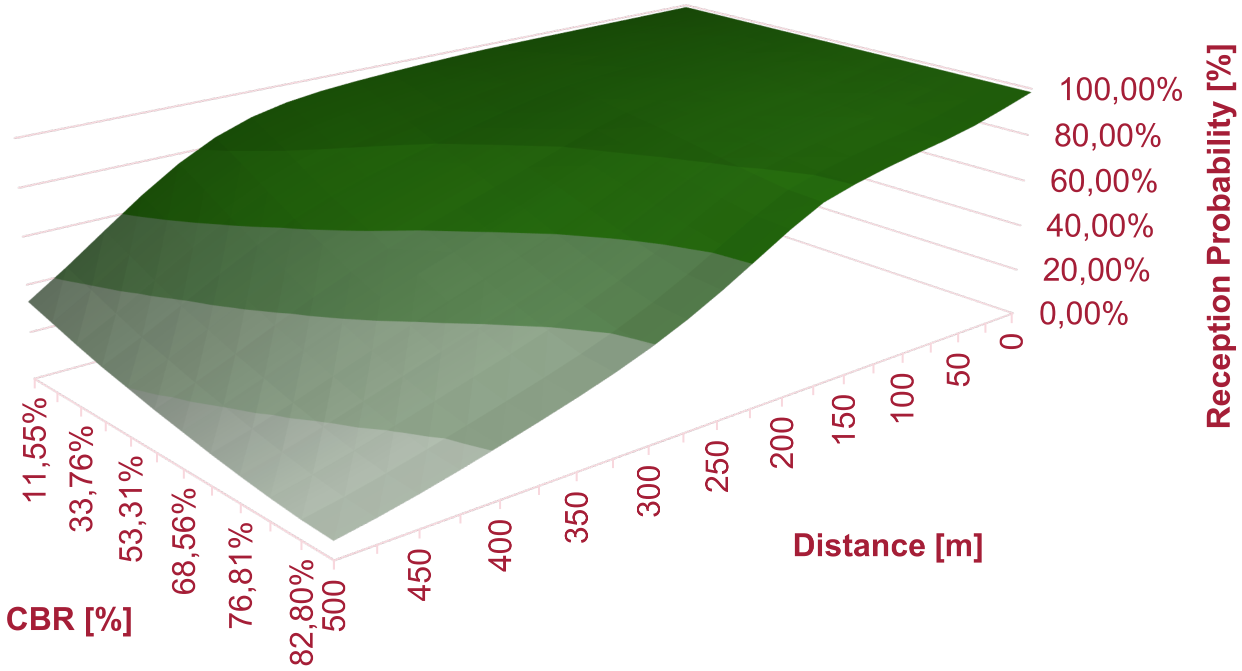


D) V2V Network Simulation

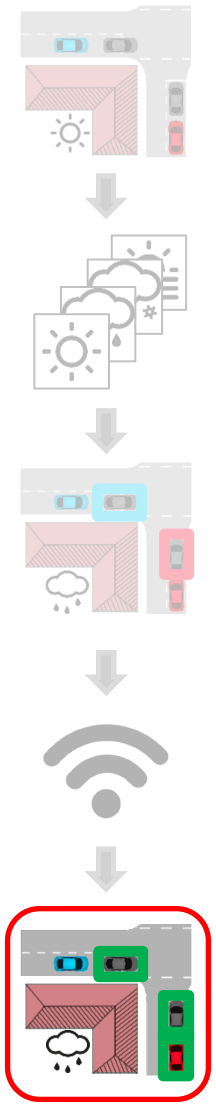


- Requirements
  - Parametrizable simulation
  - Reception probability & latency
- Analytical V2X model [Se21]:
  - Transmission interval $t_{CPM} = [100ms, 1s]$
  - CPM generation rules
    - $r_{pos} = 4\ m$
    - $r_{vel} = 0.5\ \mathrm{ms}^{-1}$
    - $r_{course} = 0.07\ rad$
    - $r_{t,vehicle} = 1s$
    - $r_{t,VRU} = 0.5s$
  - Channel busy ratio (CBR)
  - Distance between sender and receiver

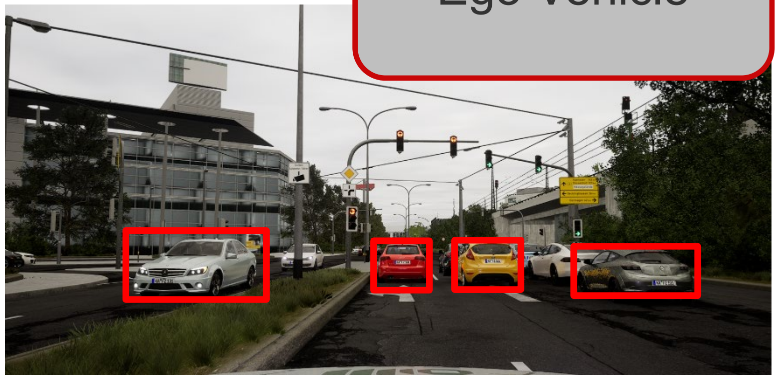
Reception Probability of Communication Model

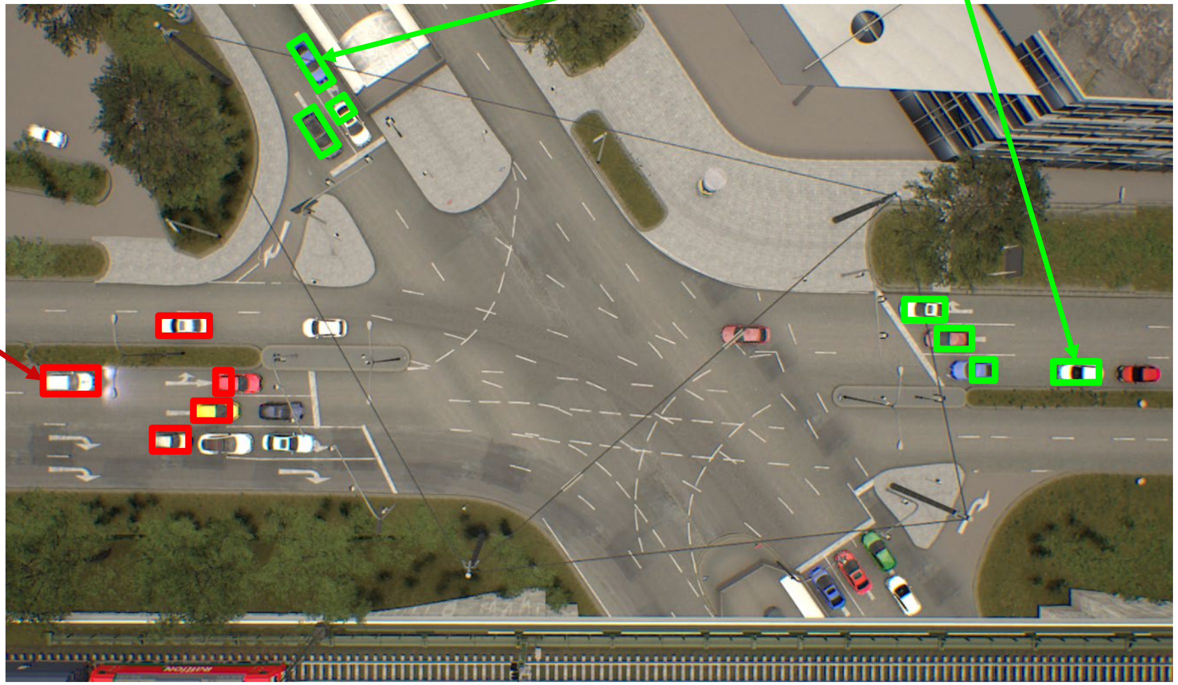


E) Collective Perception

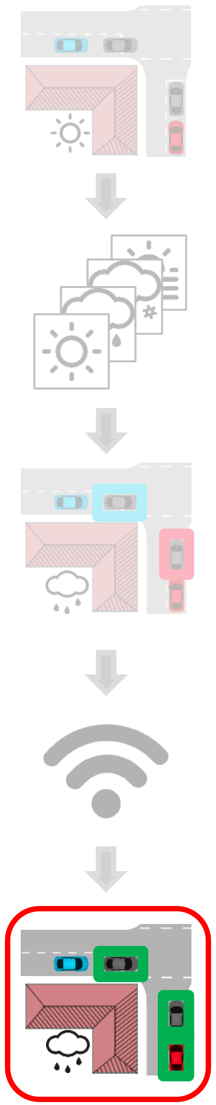


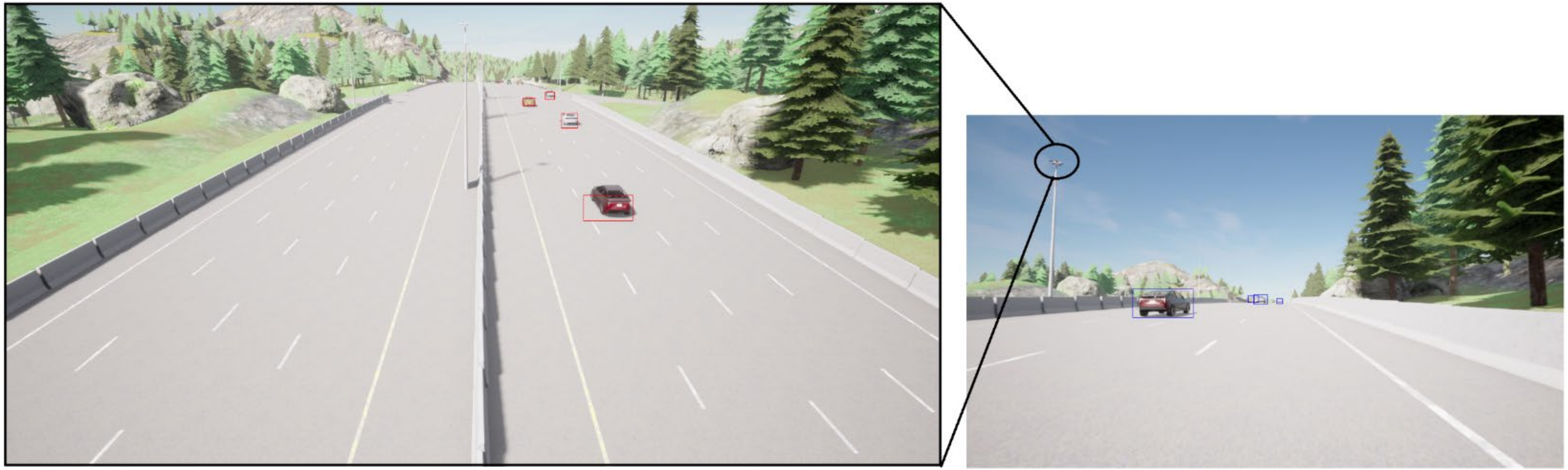
1. Alignment of communicated data
   a) Predict tracks to current timestamp & align coordinate system
2. Associate objects
   a) Hungarian Algorithm, Nearest Neighbors
3. Fuse with KF, EKF, UKF or CI
   a) CV, CA, CTRA



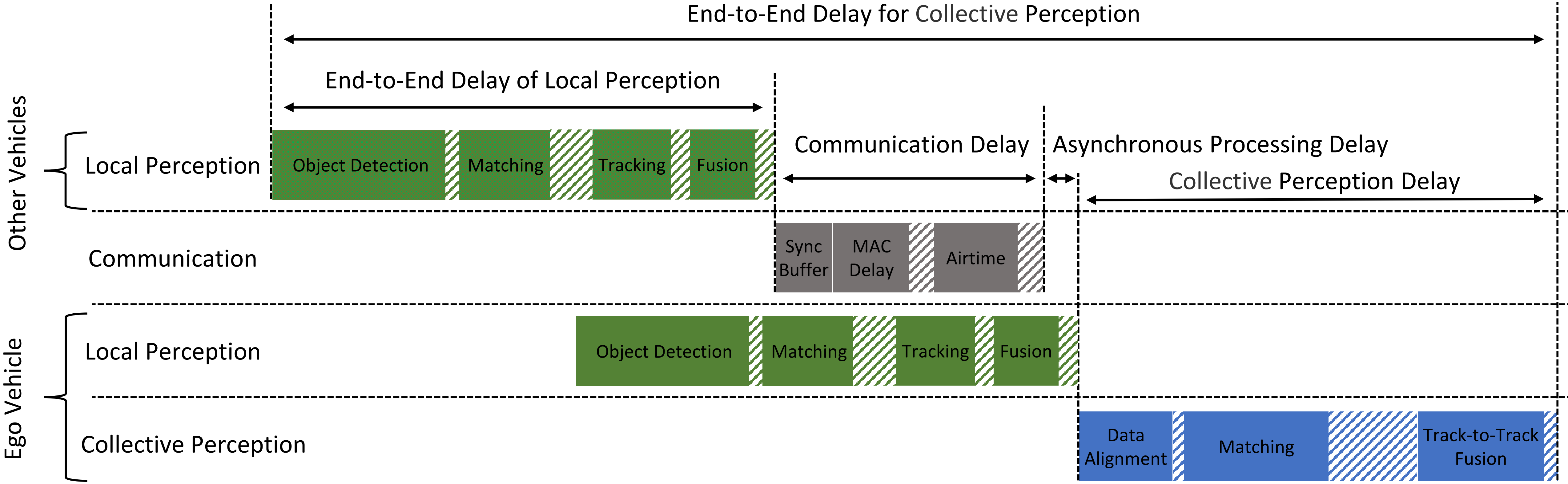


E) Collective Perception with Road Side Unit (RSU)

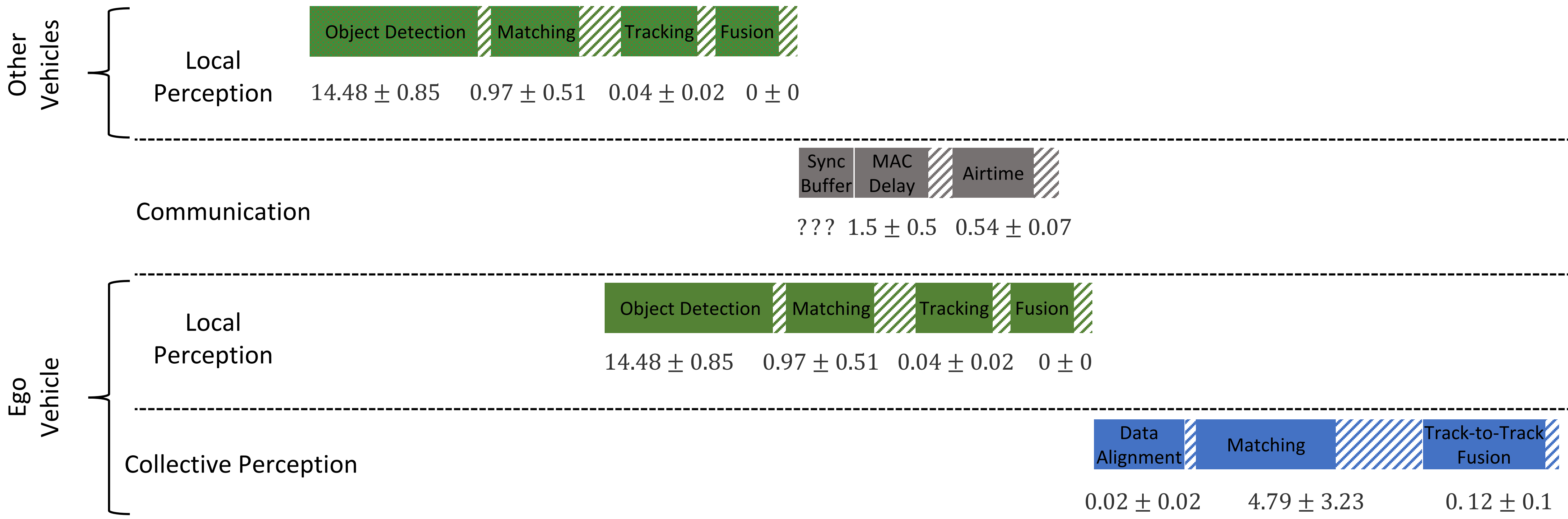




Collective Perception Pipeline – Investigation of Latencies

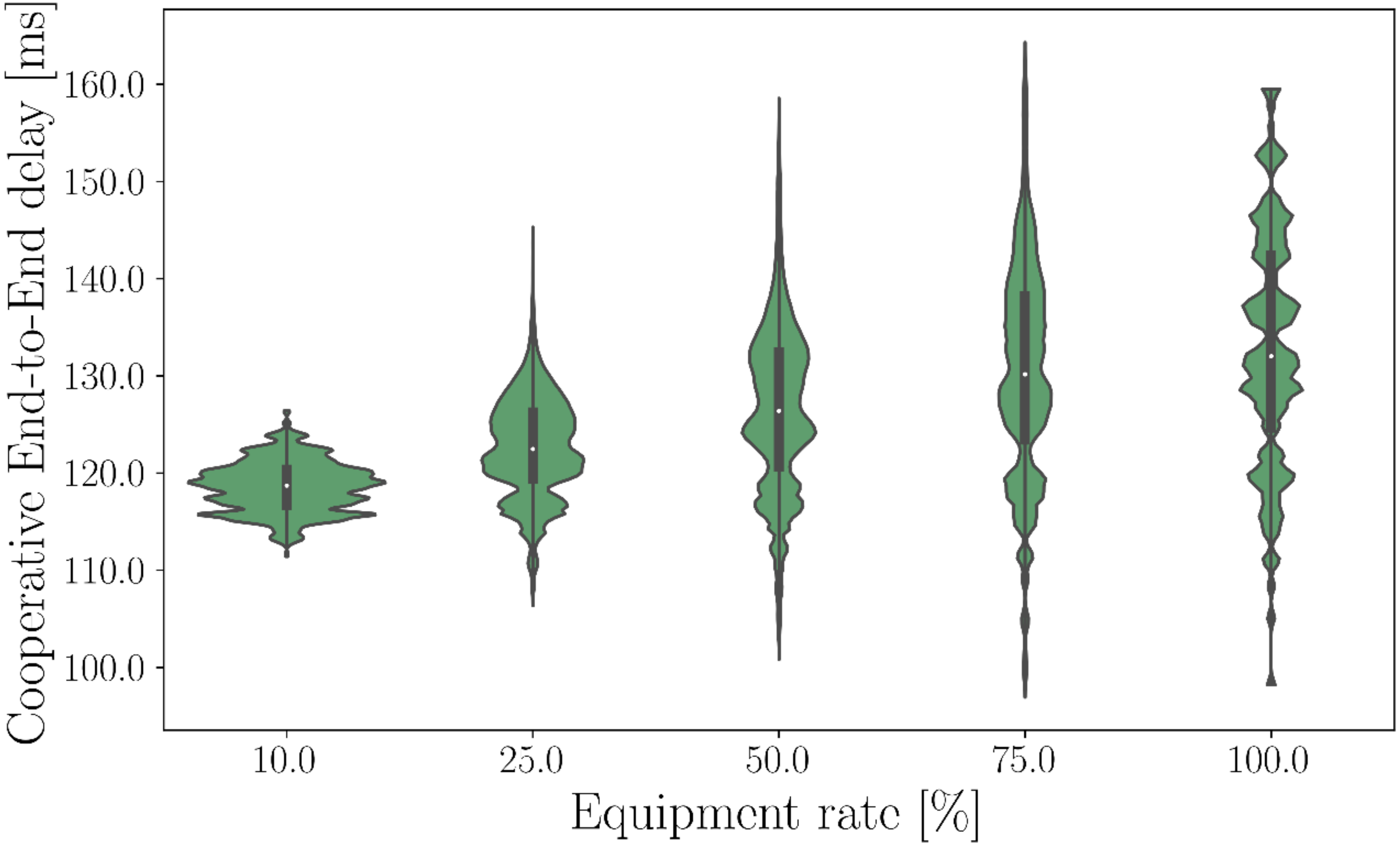


Collective Perception Pipeline – Investigation of Latencies [ms]

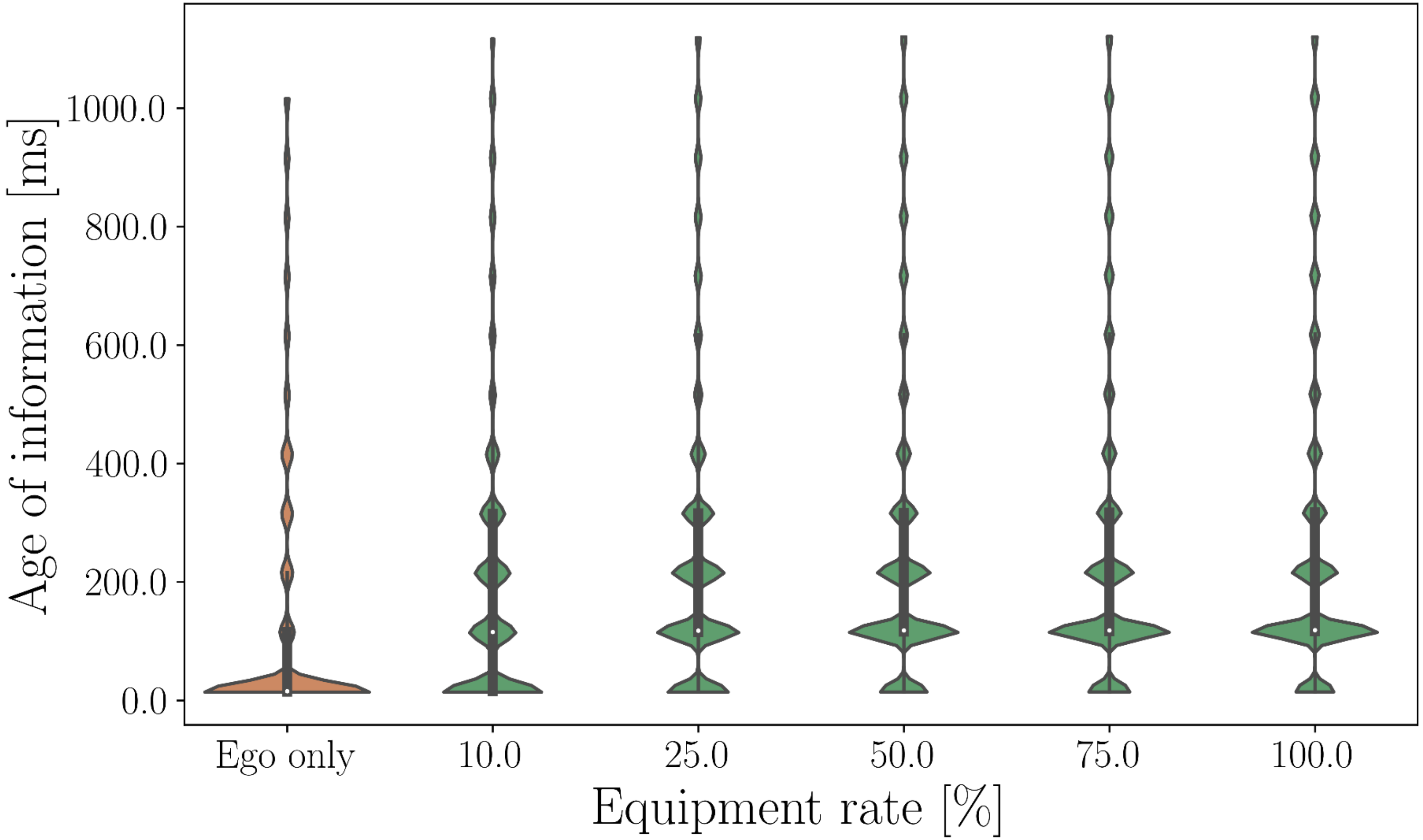


Parameter	Values
CPU	Intel-Core i7-7700K
RAM	32 GByte
GPU	RTX 2080 Ti

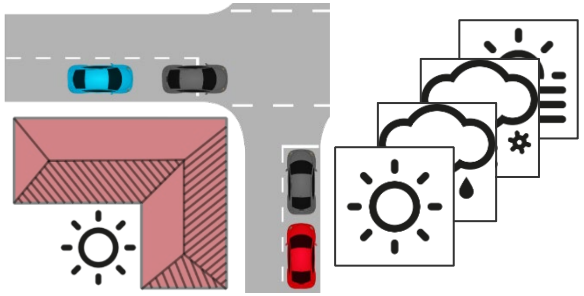
Evaluation – End-to-End Latencies



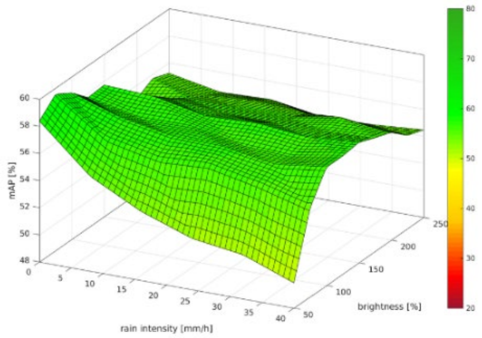
Evaluation – Age of Information

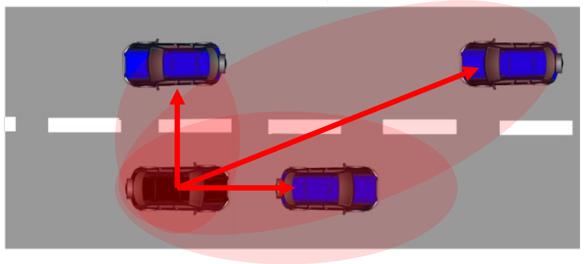


Optimization – Local & Collective



Simulation – Perception Pipeline



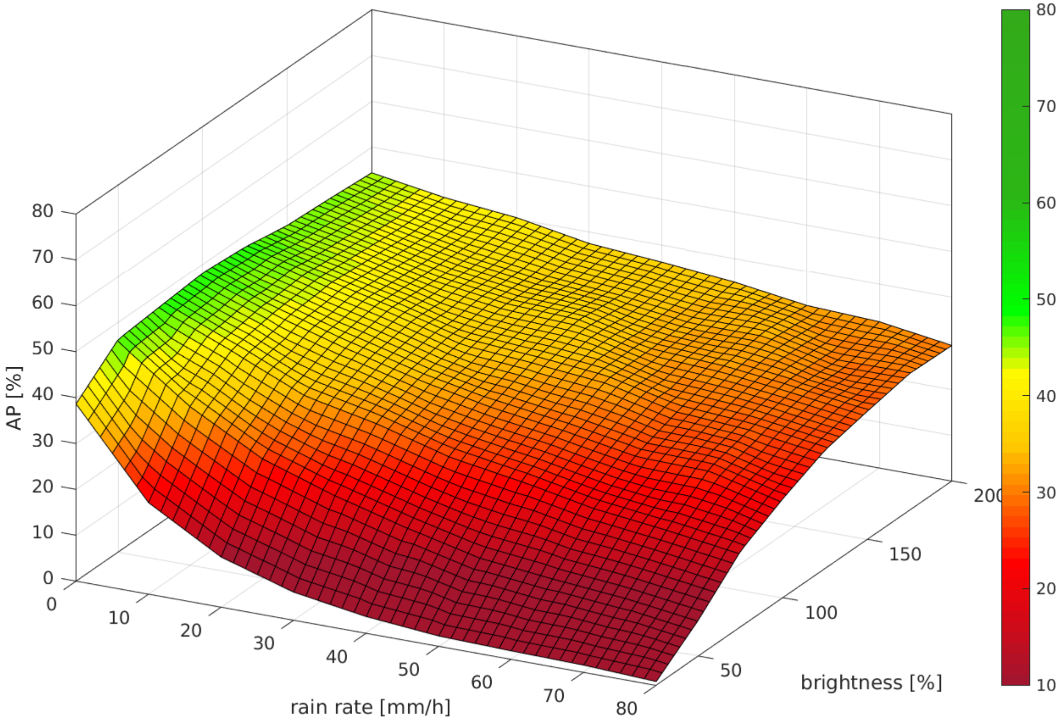


Evaluation – Safety Metric

Motivation – Local Optimization

- Robustness of CNNs strongly affected by training data!
- Common datasets contain few variation:

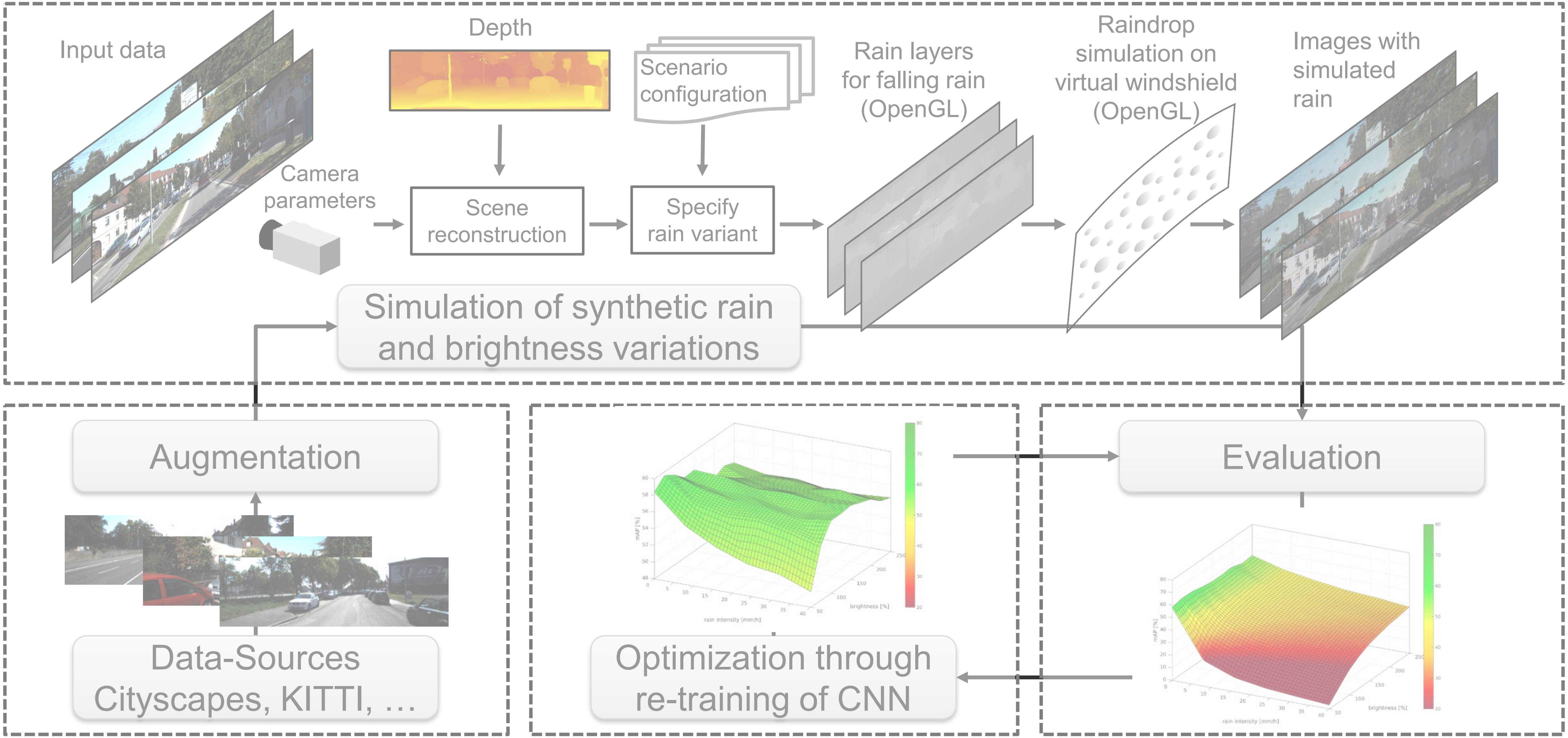
KITTI



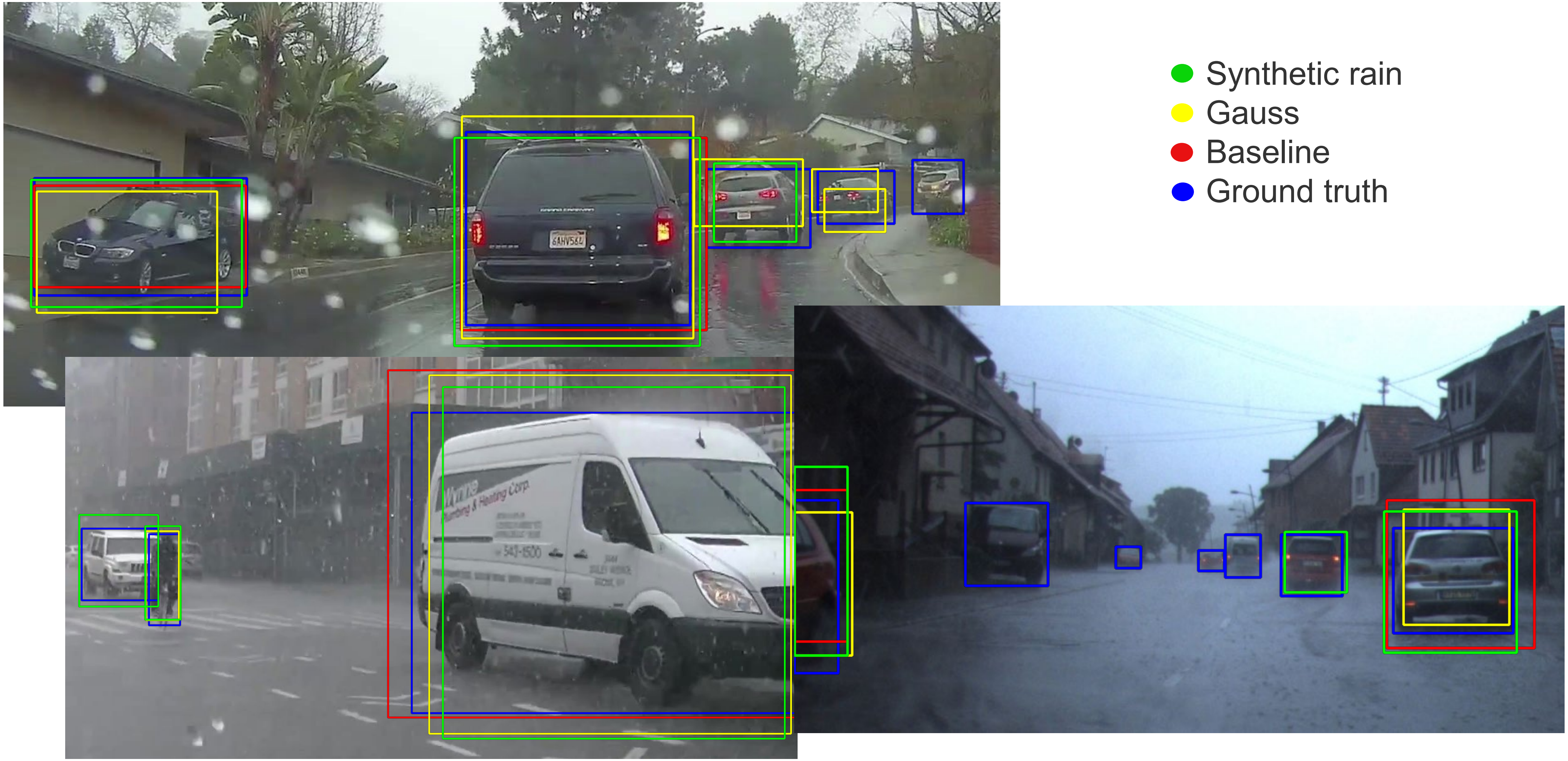
- Recording of all desired environmental conditions:
  - Not feasible and not reproducible

→**Extend existing datasets through augmentation**

Robustness Evaluation and Optimization Approach



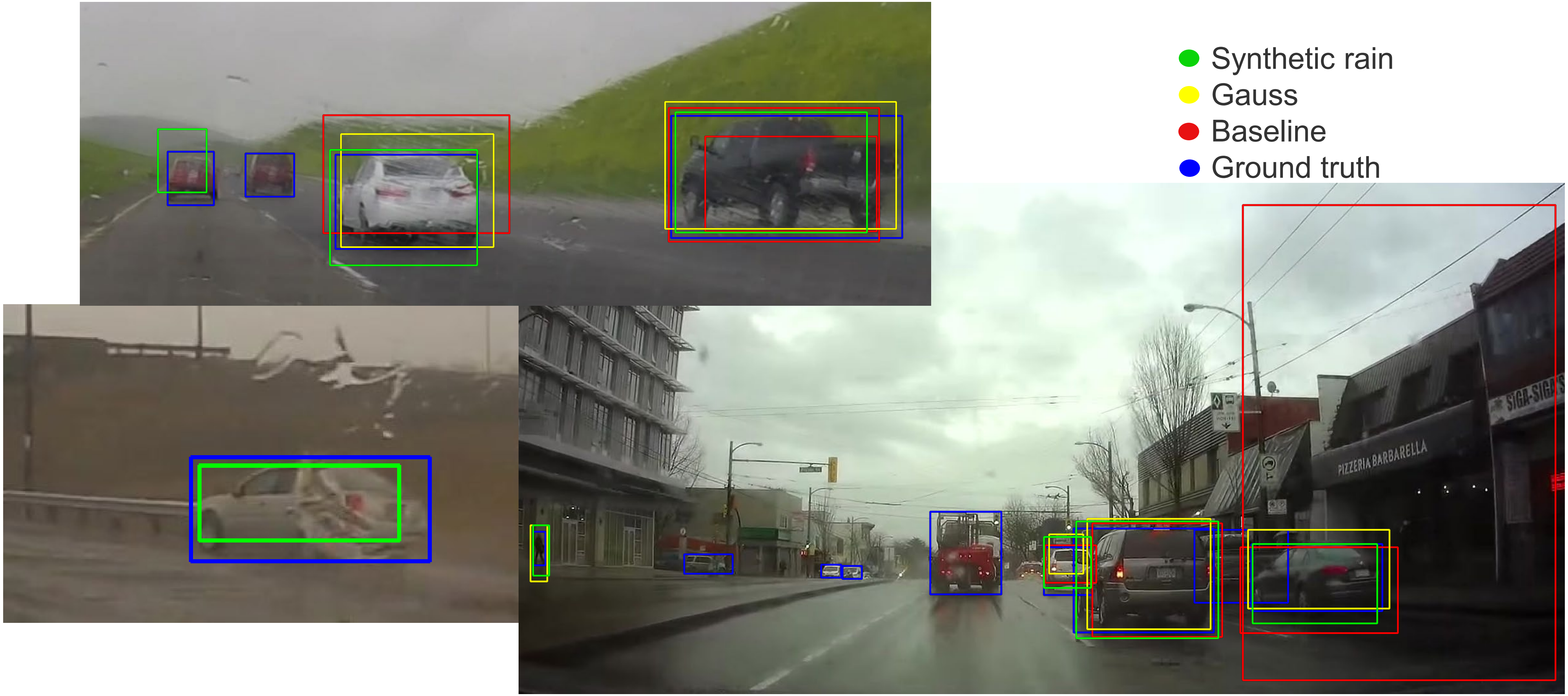
Performance of Optimized Faster R-CNN on Real Rain Dataset



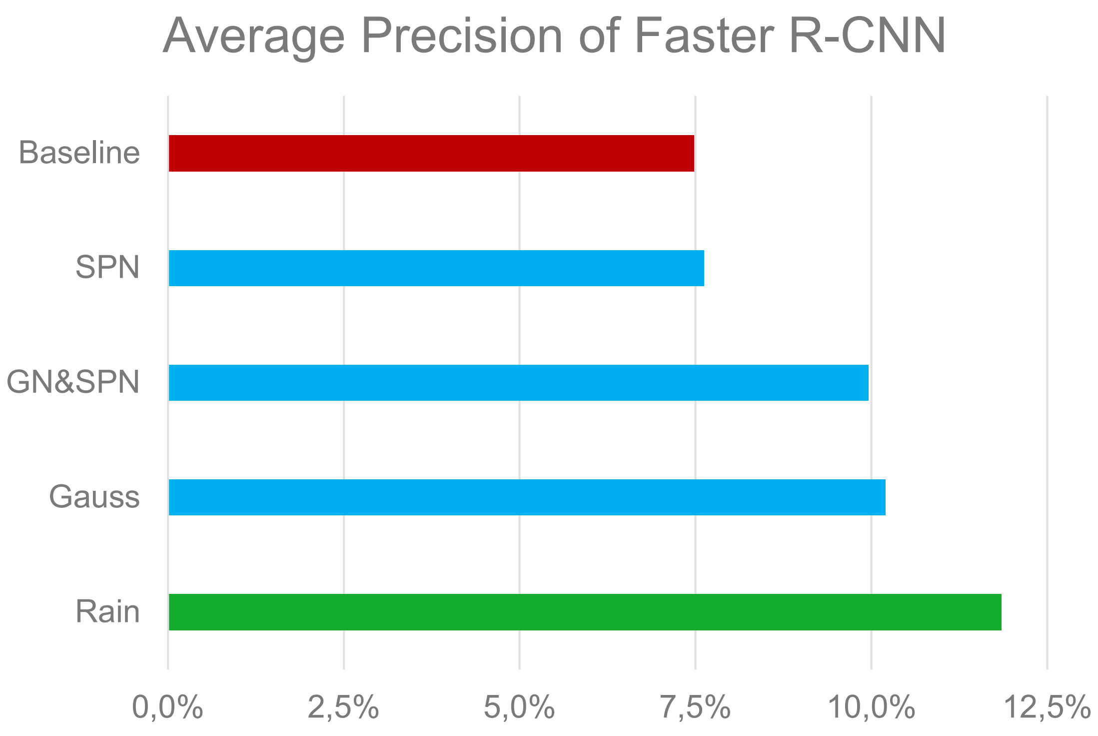
- Synthetic rain
- Gauss
- Baseline
- Ground truth

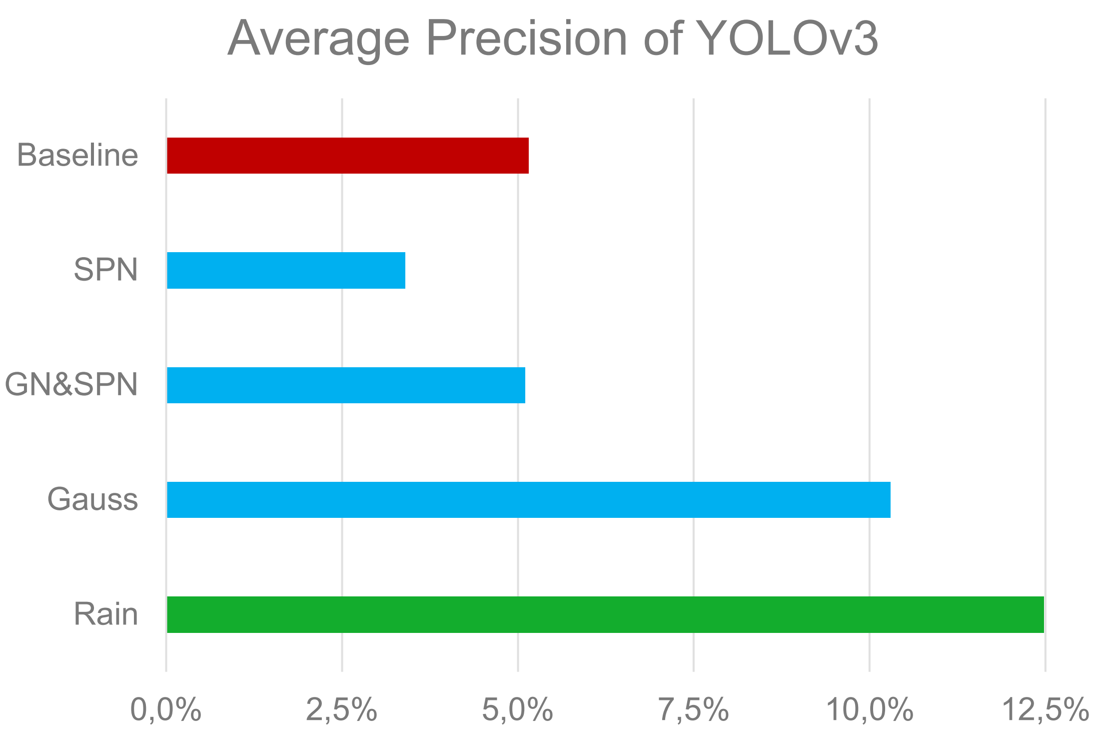
Performance of Optimized Faster R-CNN on Real Rain Dataset

- Synthetic rain
- Gauss
- Baseline
- Ground truth



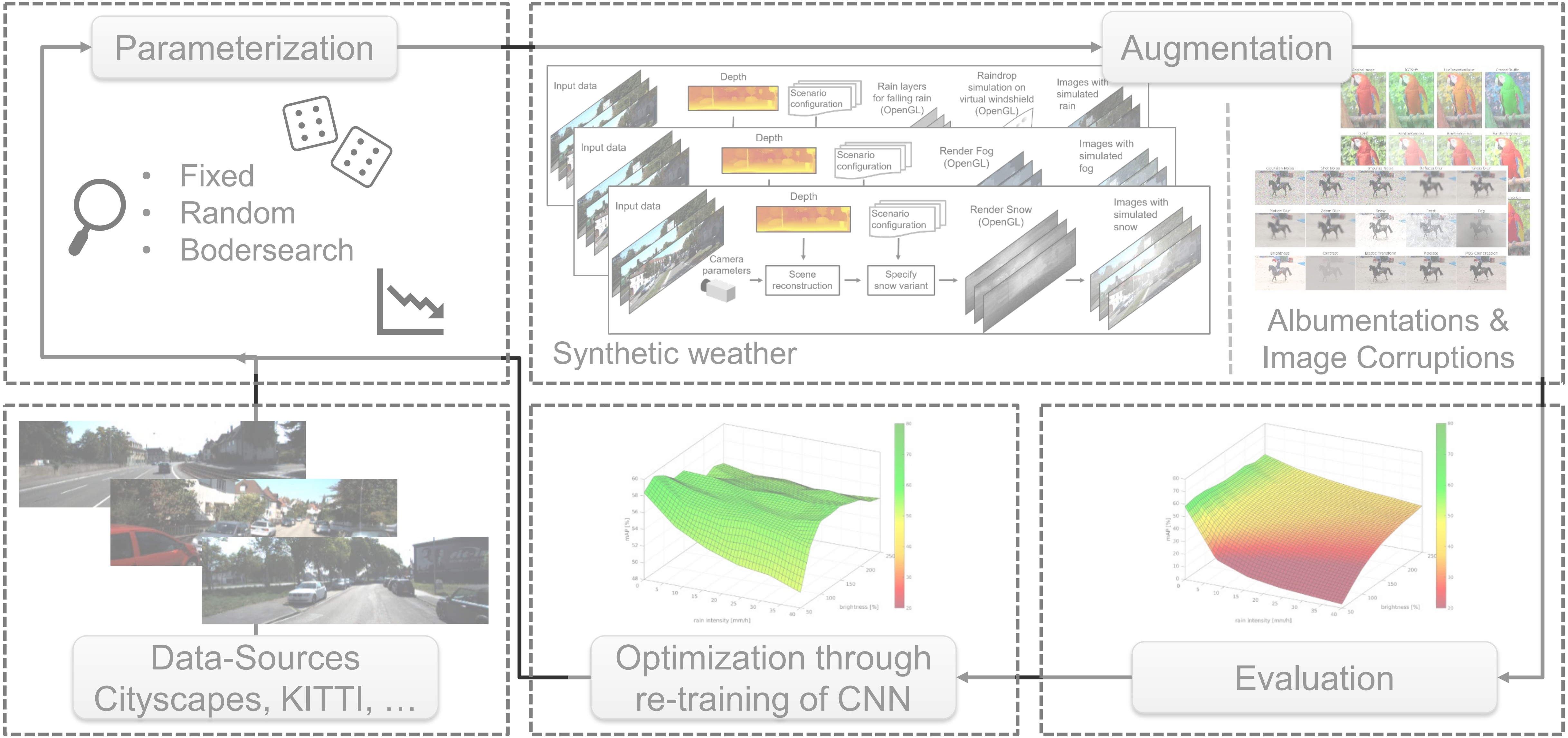
Performance on Real Rain Dataset





- Rain variations perform best for either network
- **Improve** baseline AP for
  - Faster R-CNN by **4.37 p.p.**
  - YOLOv3 by **7.33 p.p.**

Improved Robustness Evaluation and Optimization Approach

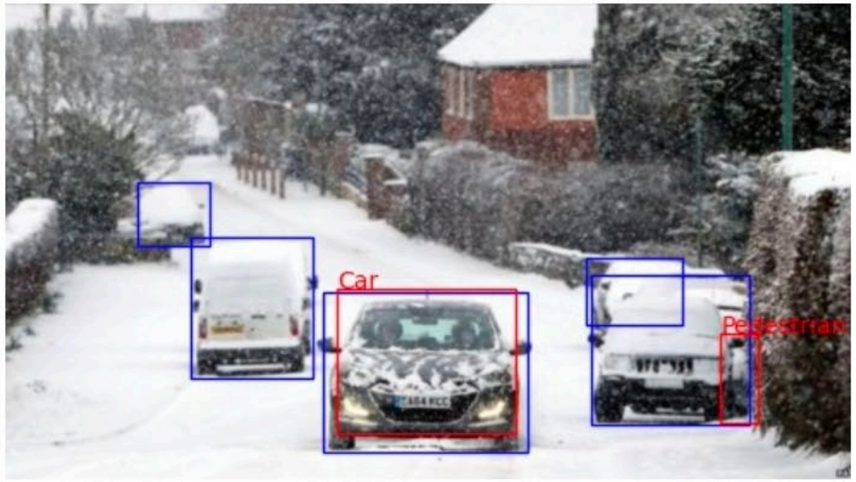


Average Precision – Specific Weather Optimization

	Synthetic Snow random	Synthetic Snow Bordersearch	Image Corruptions Snow	Albumentations	Synthetic Snow random + Albumentations	Synthetic Snow Bordersearch + Albumentations	Baseline
KITTI	66.39%	66.02%	67.92%	**68.06%**	66.34%	66.61%	66.93%
DAWN Snow	15.70%	13.99%	10.05%	16.56%	22.88%	**23.75%**	8.05%

Results – Specific Weather Optimization

(a) KITTI



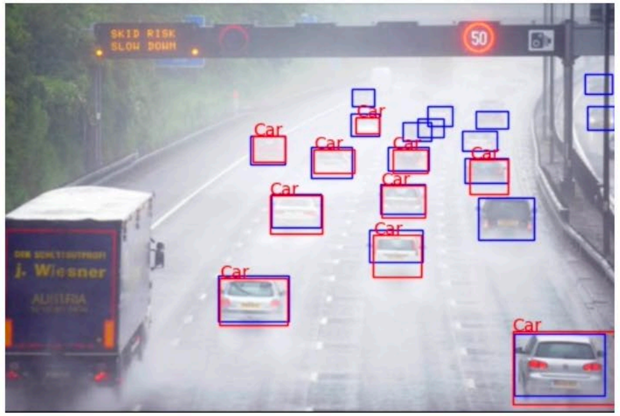
(a) Dawn snow

Average Precision – Combined Weather Optimization

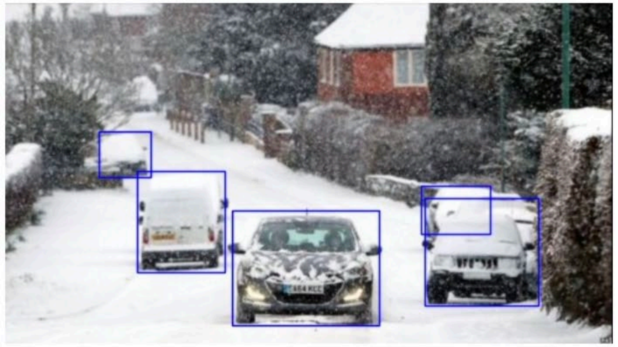
	Synthetic Weather random	Synthetic Weather Bordersearch	Albumentations	Synthetic Weather random + Albumentations	Synthetic Weather Bordersearch + Albumentations	Baseline
KITTI	67.47%	66.90%	**68.06%**	66.98%	66.44%	66.93%
Real Rain	22.01%	24.90%	27.17%	**27.84%**	27.57%	16.31%
DAWN Rain	18.85%	19.51%	17.38%	**23.46%**	20.79%	8.60%
DAWN Snow	16.95%	16.42%	16.56%	**24.52%**	22.21%	8.05%
DAWN Fog	17.08%	21.19%	19.00%	**28.66%**	21.79%	5.45%

Results

(a) Real rain



(b) Dawn rain



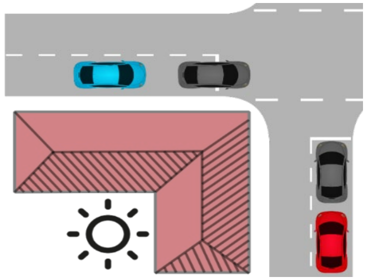
(c) Dawn snow

(d) Dawn fog

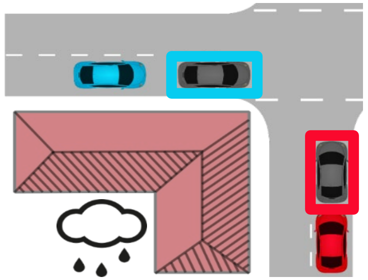
(d) KITTI

Motivation – Collective Optimization

A) Scenario



C) Local Perception

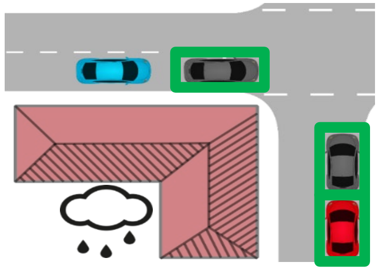


- FP/FN detections
- Inaccurate state estimations

D) V2V Communication

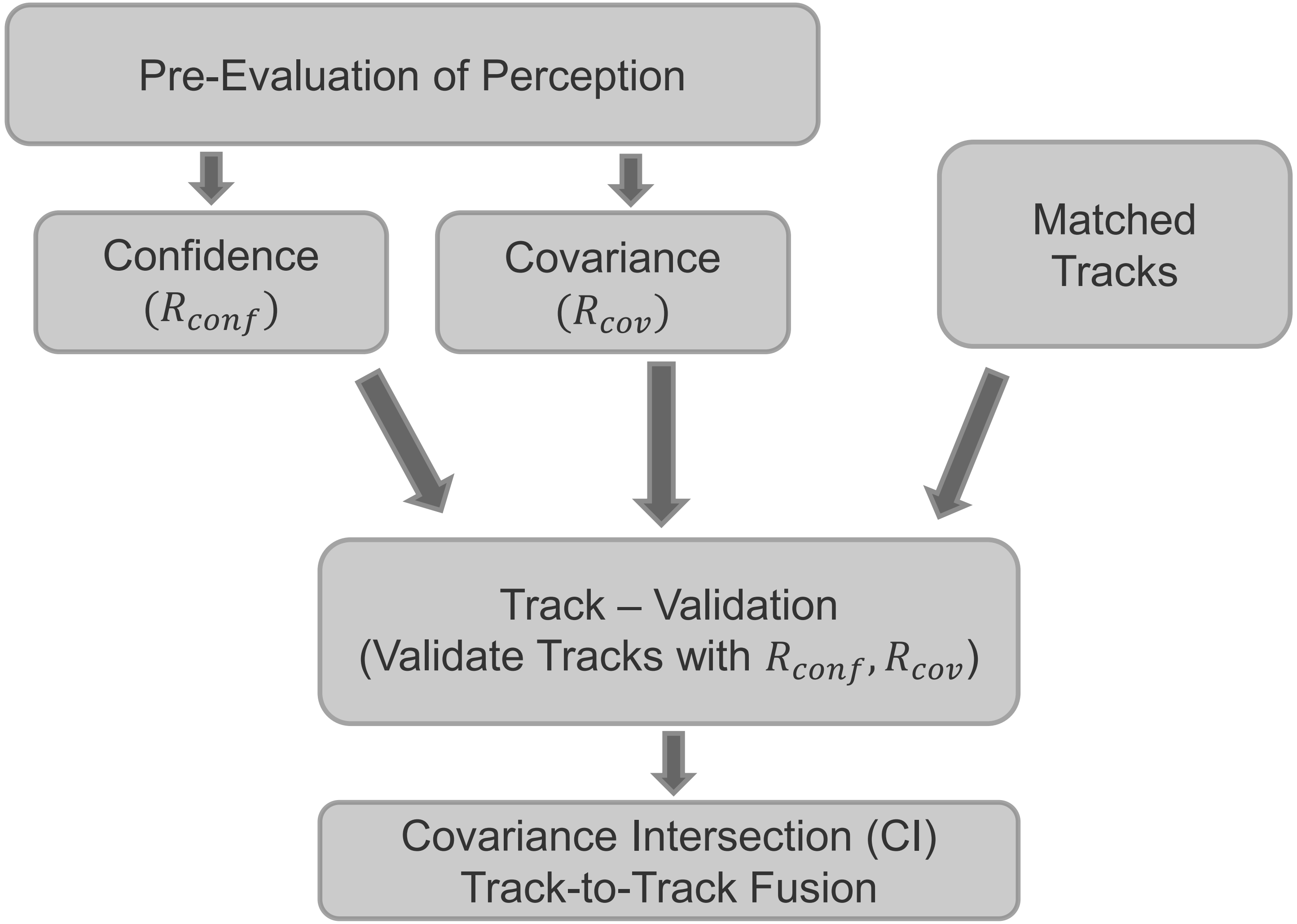
- Limited communication channel
- Malicious data from an attacker

E) Collective Perception



→ inaccurate/wrong fusion result

→ **Idea:** validity and trustworthiness validation before fusion

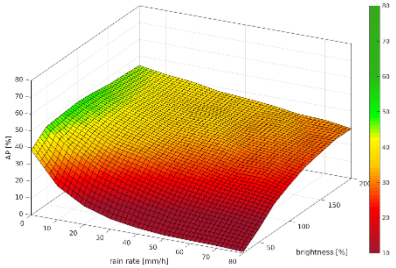

Pre-Evaluation of Perception
Confidence (R_{conf})
Covariance (R_{cov})
Matched Tracks
Track – Validation (Validate Tracks with R_{conf}, R_{cov})
Covariance Intersection (CI) Track-to-Track Fusion

Pre-Evaluation: Gathering Reference Data

Simulation

- **Assumption:** All coop. vehicles use same sensor setup and algorithms

Evaluation



- Recall as confidence
- Deviation in state estimation
  - Position
  - Velocity

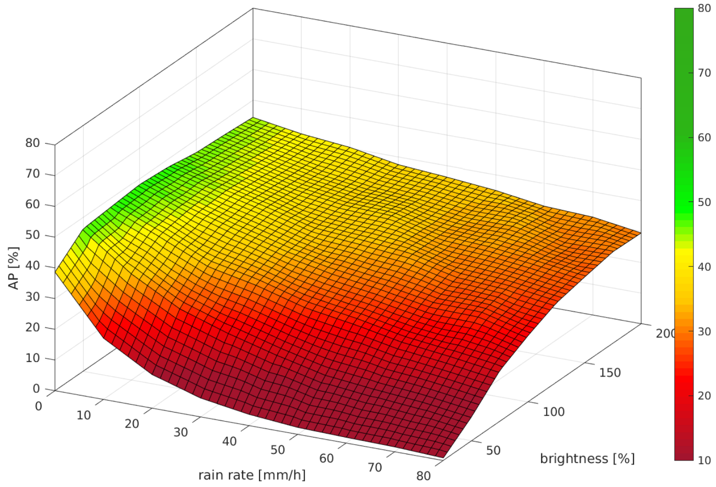
Reference data

- Reference data (distances and weather conditions)
  - Confidence matrix
  - Covariance matrix (position and velocity variances)

Confidence based Optimization Strategies

- **2TracksConf:**
  two tracks with highest confidence
  → Reinhardt et al. [Re15] showed that CI with multiple tracks not necessarily optimal

- **FilterConf:**
  deviation of track confidence < threshold of reference



Covariance-based Optimization Strategies

- **2TracksCov:**
  Two tracks with smallest covariance matrix (CM)
  → Reinhardt et al. [Re15]

- **FilterTrace:**
  deviation trace tr(CM) < threshold of reference

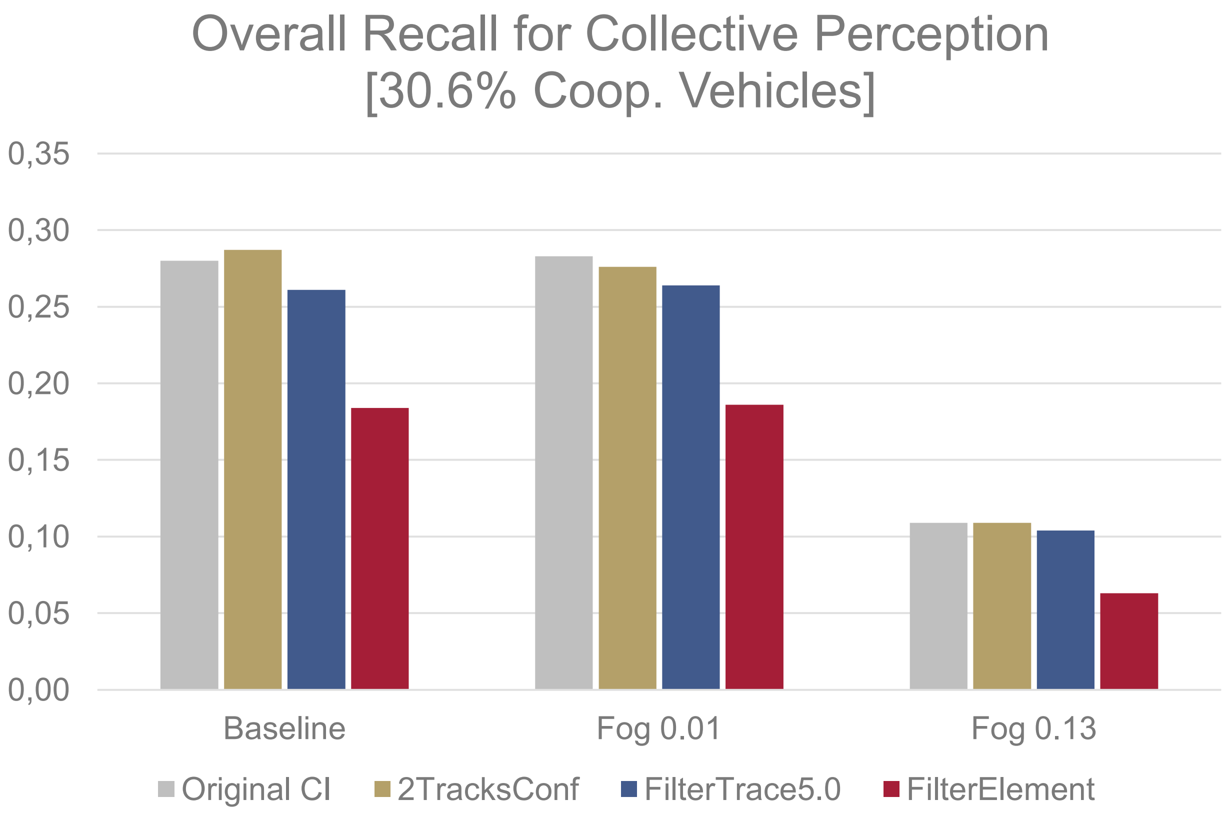
$$\mathrm{R}_{\mathrm{cov}} = \begin{pmatrix} \sigma^2_{p.x} & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{p.y} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{p.z} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{v.x} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{v.y} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{v.z} \end{pmatrix}$$

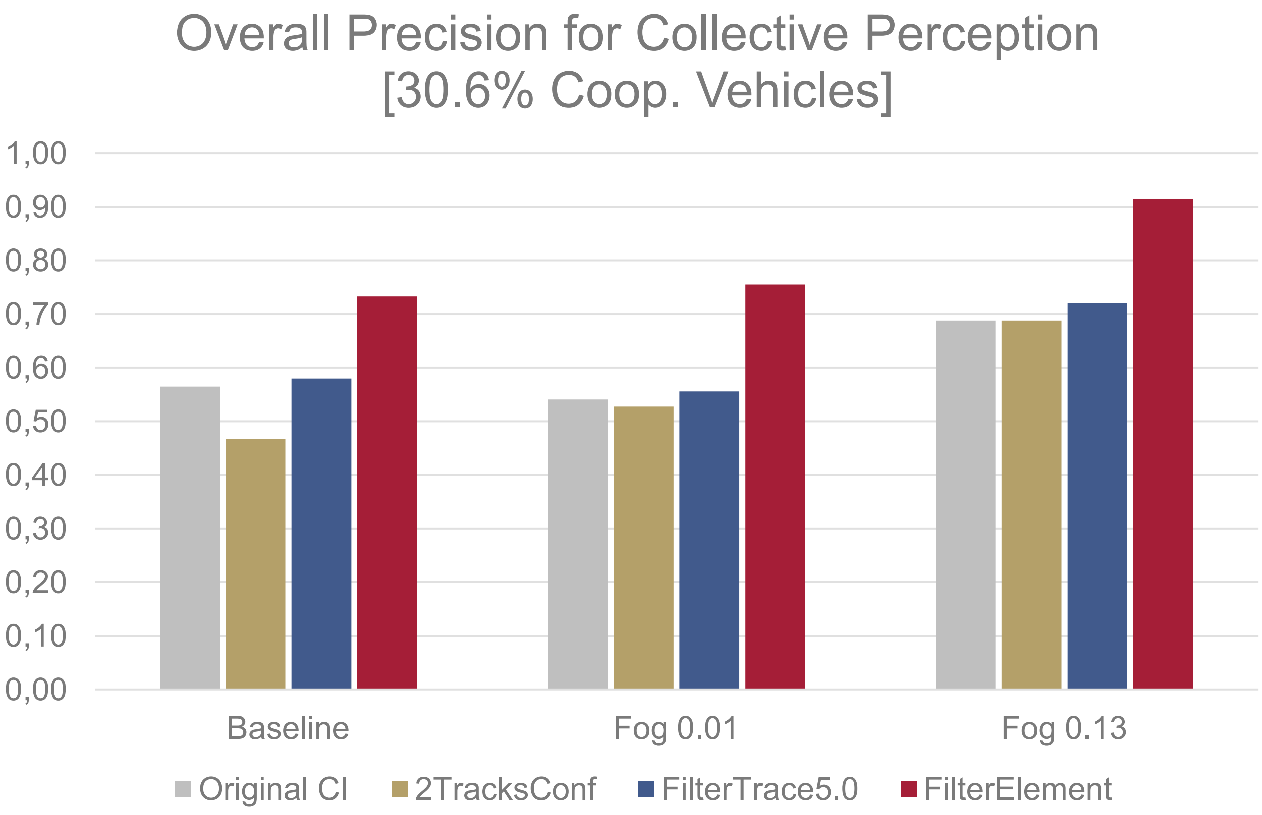
- **FilterElementwise:**
  elements of main diagonal for validation

$$\mathrm{R}_{\mathrm{cov}} = \begin{pmatrix} \sigma^2_{p.x} & 0 & 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{p.y} & 0 & 0 & 0 & 0 \\ 0 & 0 & \sigma^2_{p.z} & 0 & 0 & 0 \\ 0 & 0 & 0 & \sigma^2_{v.x} & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{v.y} & 0 \\ 0 & 0 & 0 & 0 & 0 & \sigma^2_{v.z} \end{pmatrix}$$

*tr = sum over main diagonal

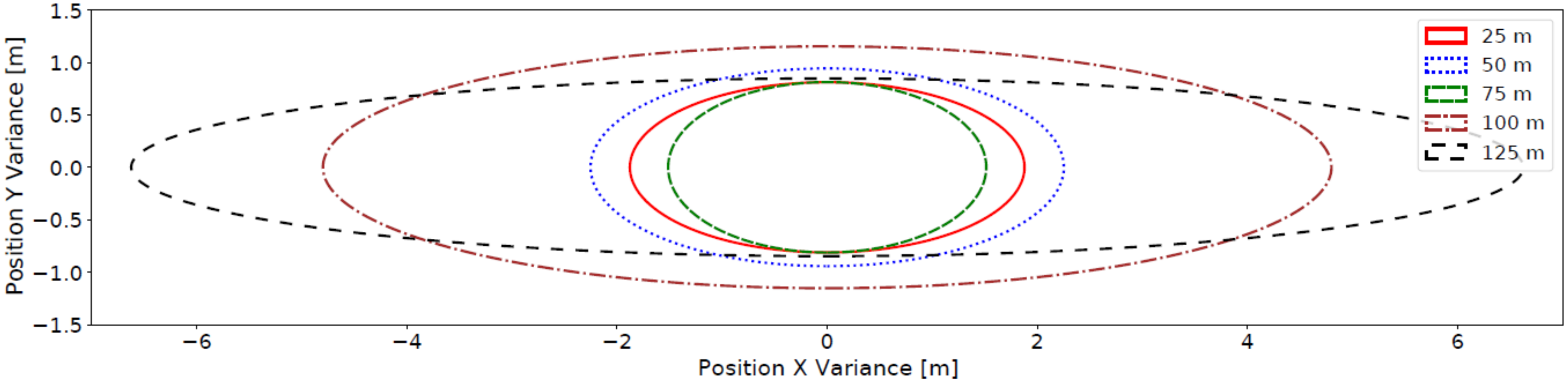
Results



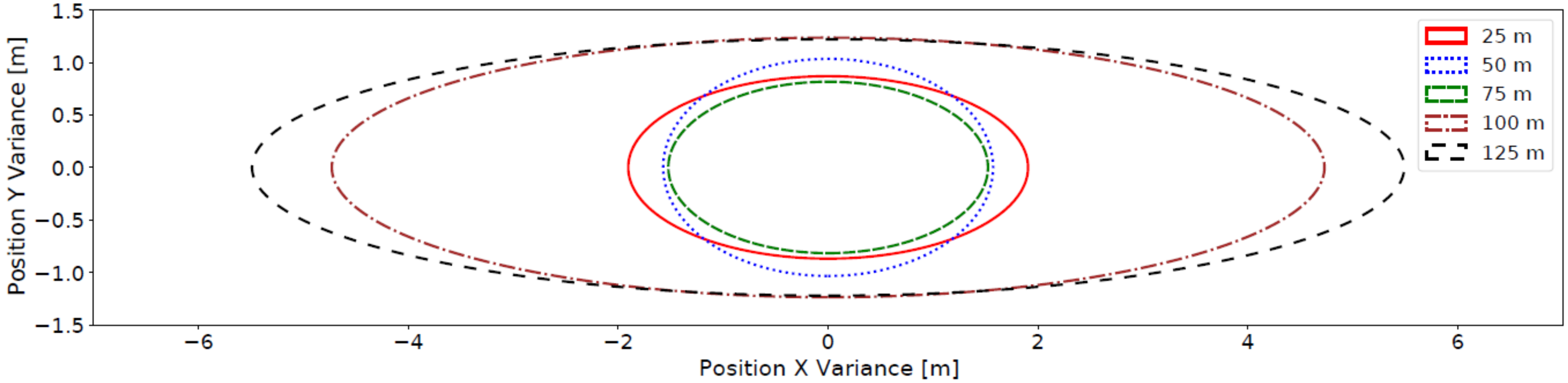


Baseline = Cloudy day without rain

Results

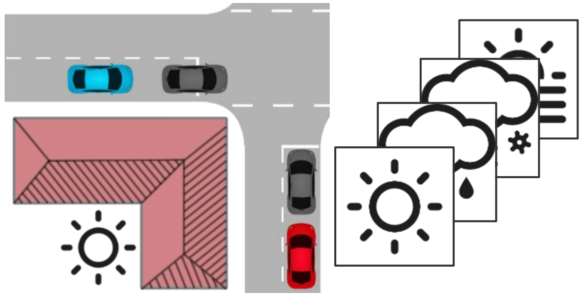


(a) *Baseline* evaluation for cloudy daytime environment and 30.6% coop. vehicles

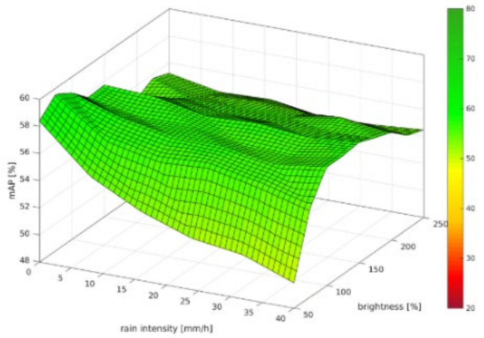


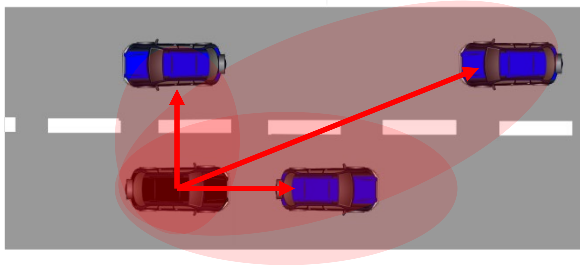
(b) *2TracksCov* evaluation for cloudy daytime environment and 30.6% coop. vehicles

Optimization –
Local & Collective



Simulation –
Perception
Pipeline





Evaluation –
Safety Metric

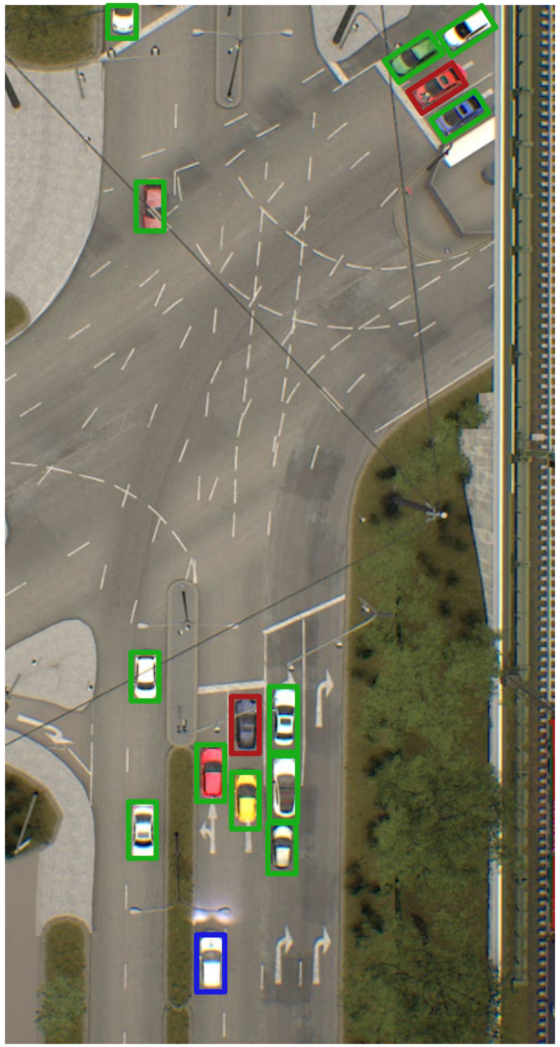
Motivation

- Vehicle approval needs safety guarantee
- Current performance metrics do not consider safety

Currently
- Evaluation of perception with performance metrics

Problem
- Case study:
  12 of 14 correctly perceived
  → Precision = 100%, Recall = 85%

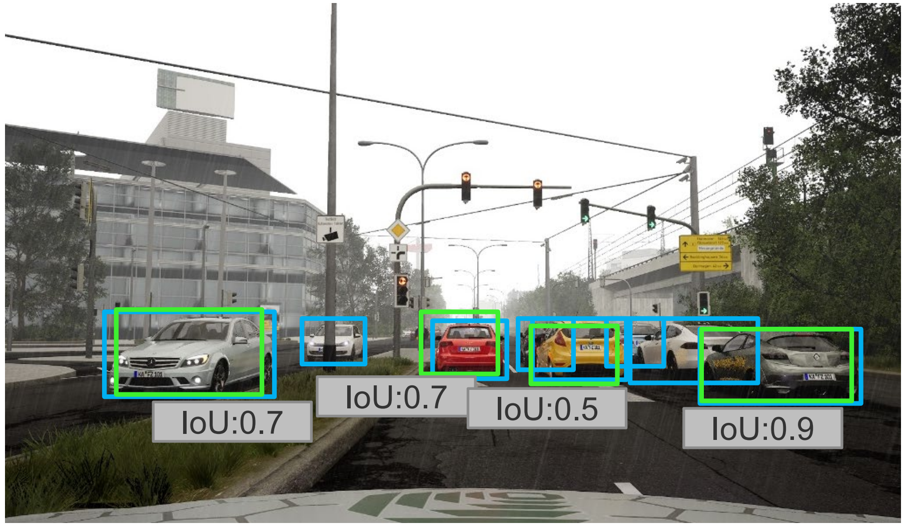
Goal
- Easily comparable safety measure



Ego vehicle
Detected
Not detected

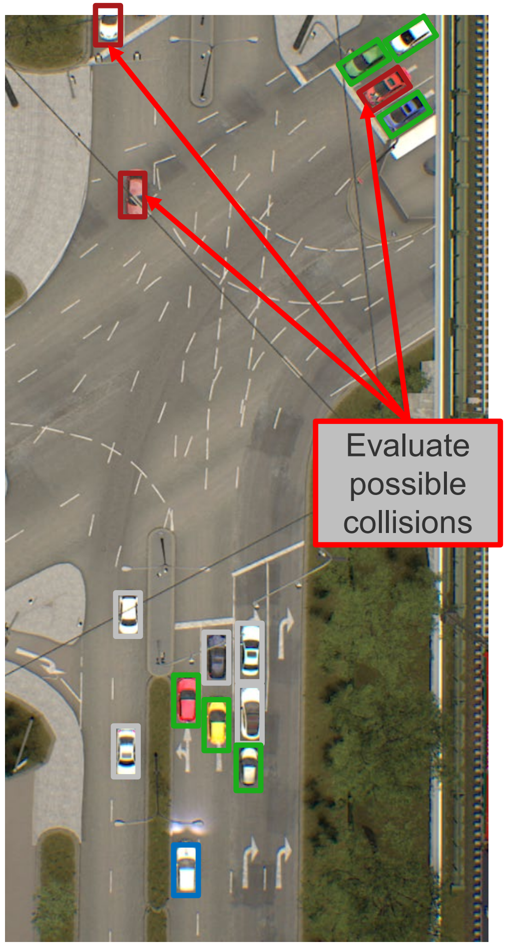
Safety Metric – Concept

1. Perception quality



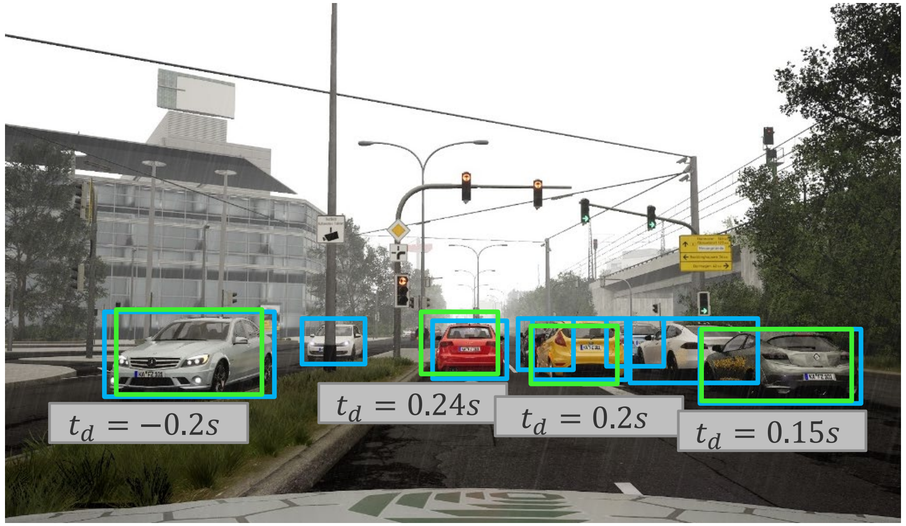
Ground truth Detection

2. Relevance of objects



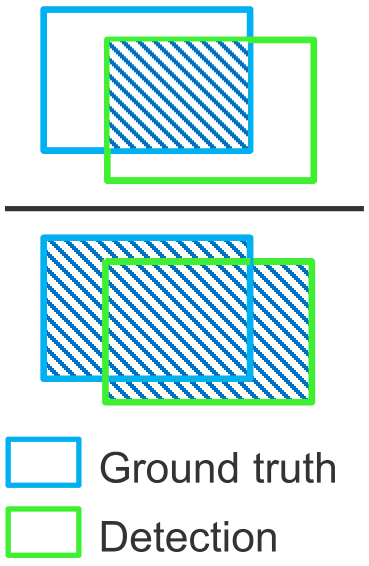
Ego vehicle Relevant
Detection Not relevant

3. Detection time



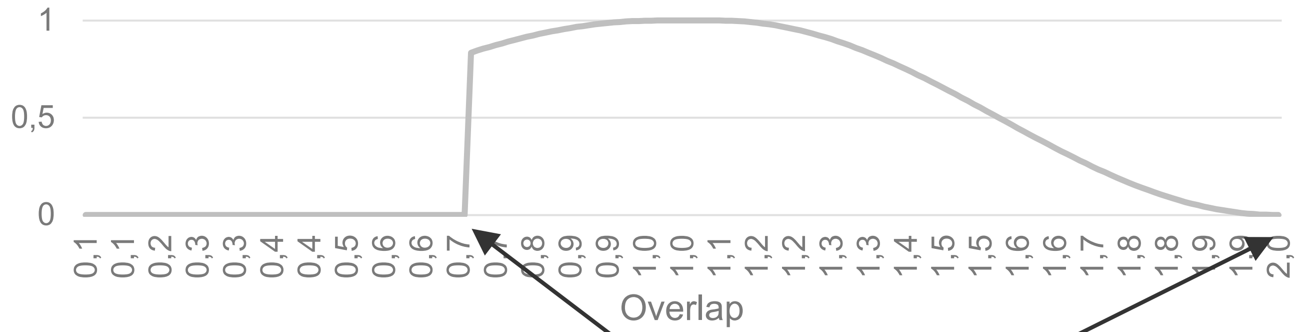
Ground truth Detection t_d: *detection time*

Safety Metric – 1. Detection & Tracking Quality



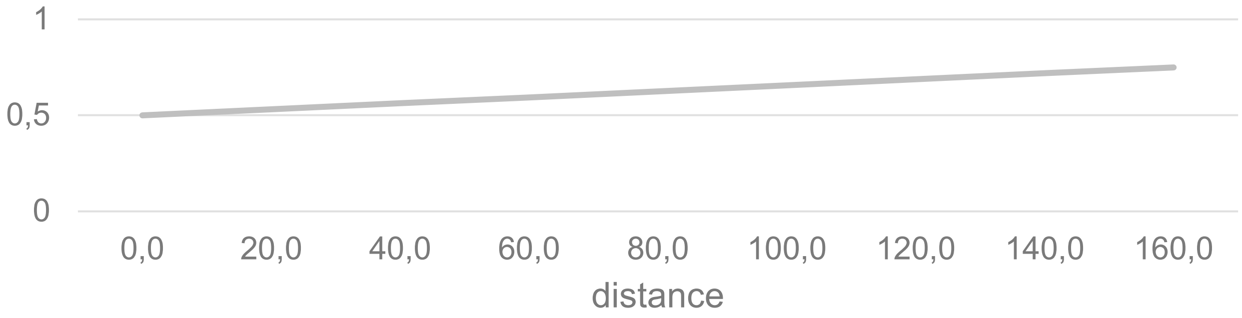
Detection	Tracking
f_v → MODA & MODP	MOTA & MOTP

Detection quality scaling factor

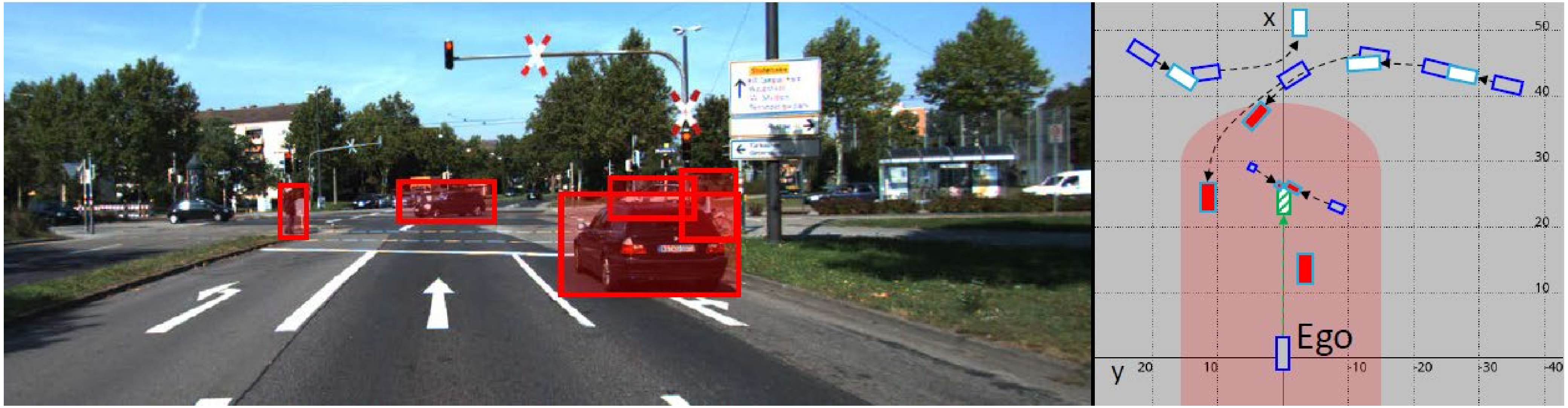


Thresholds parametrizeable

Distance based safety



Safety Metric – 2. Relevance of Objects



Source: KITTI Data set

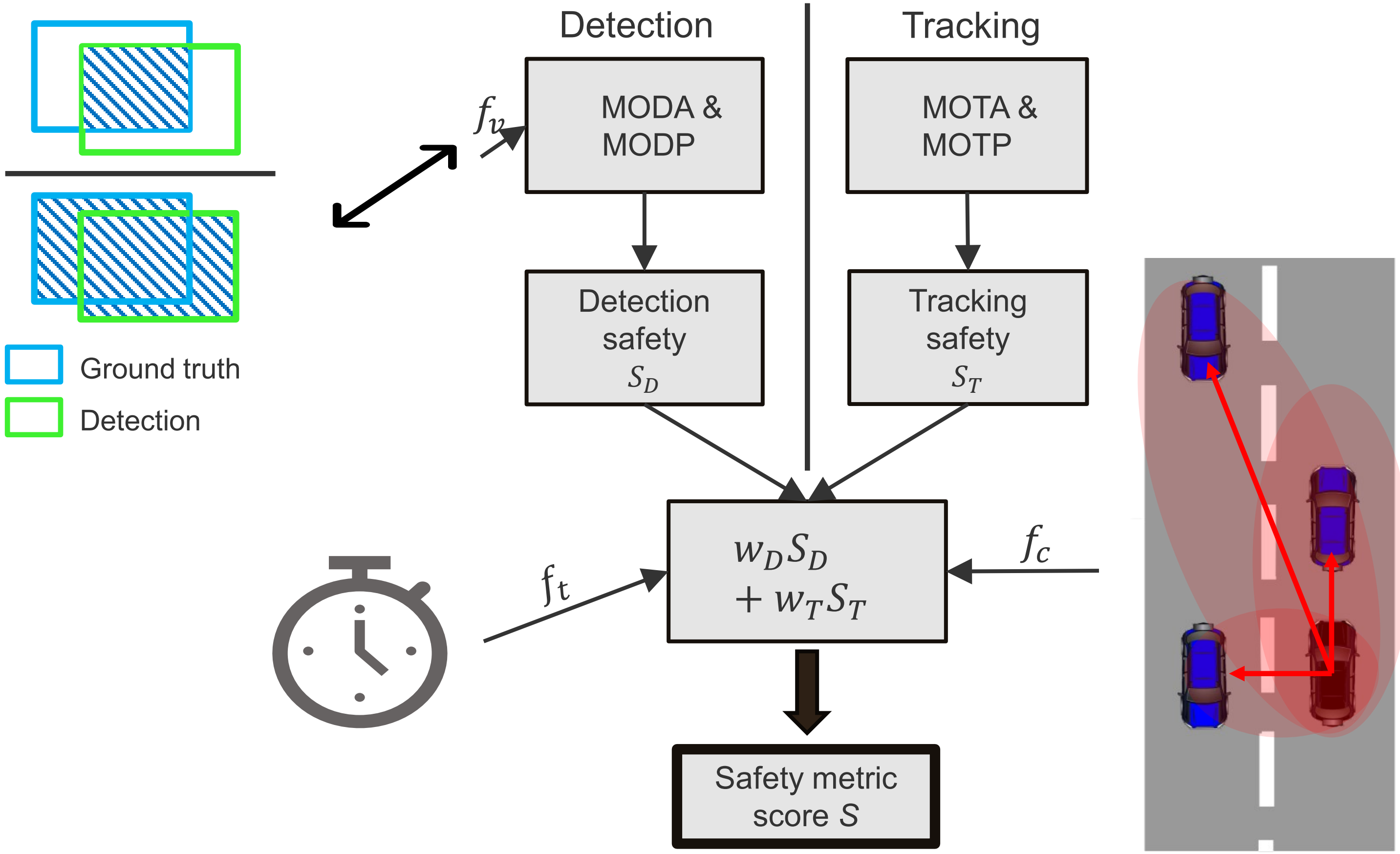
- Individual evaluation for each object
  - Position prediction

- Object undetected and safety distance (based on RSS) not given
  → possible collision

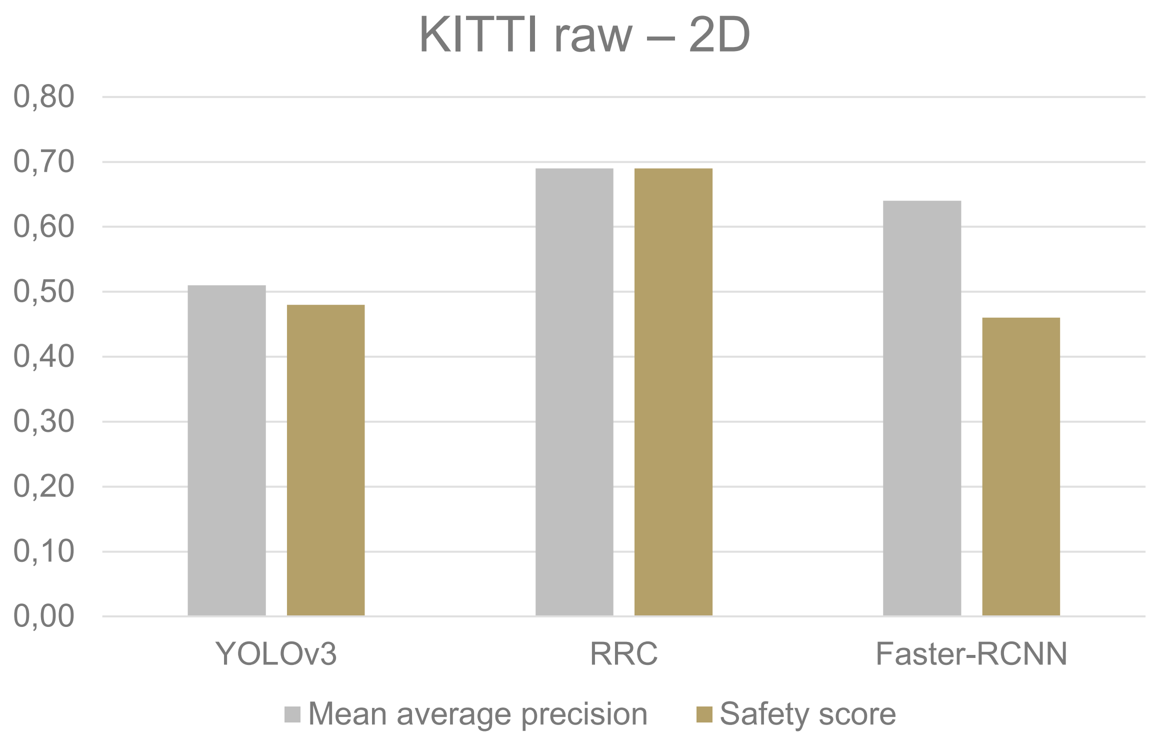
- Evaluate effect of possible collisions (velocity & object type)
  → Take worst collision as f_c

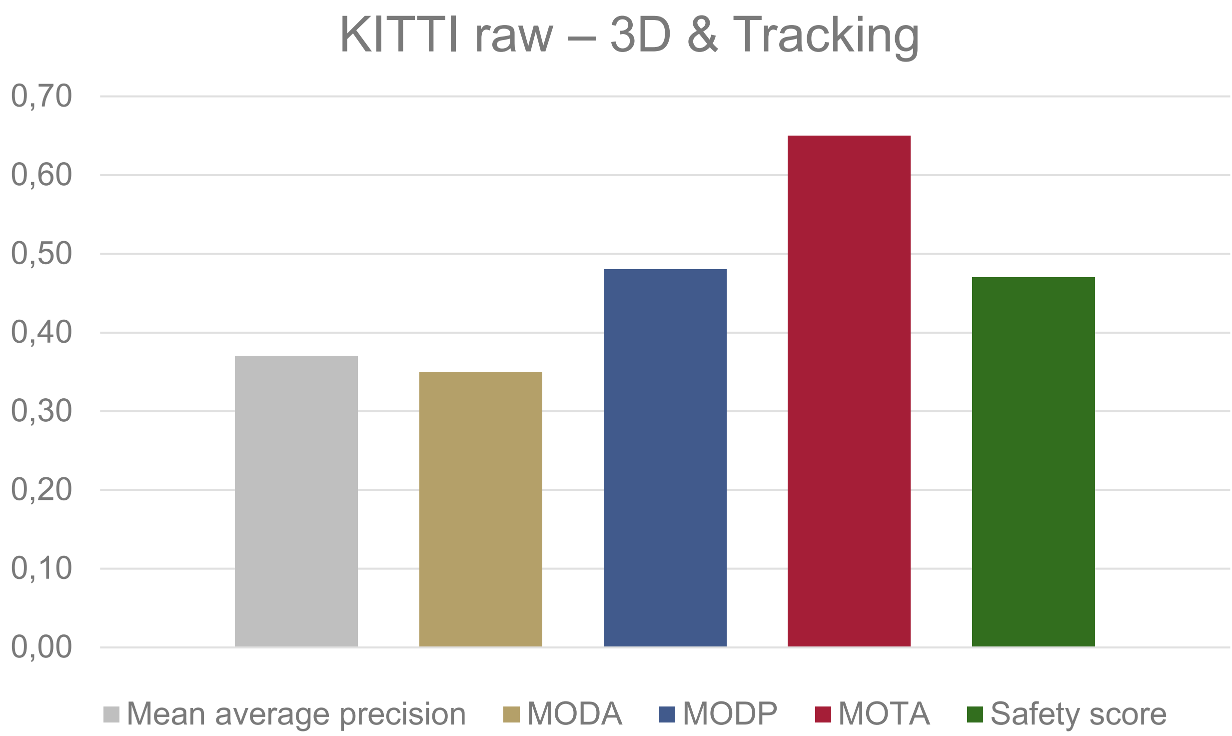
Safety Metric

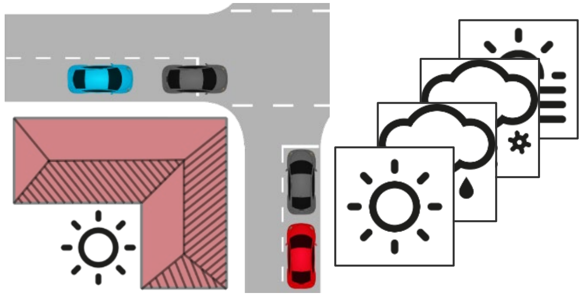
- Single & easy to compare *safety score S*
- Variability in evaluation:
  - Detection & tracking
  - Image plane & 3D detection
  - Local & collective perception
- Parametrizable
- Adaptable to different use cases and scenarios



Results

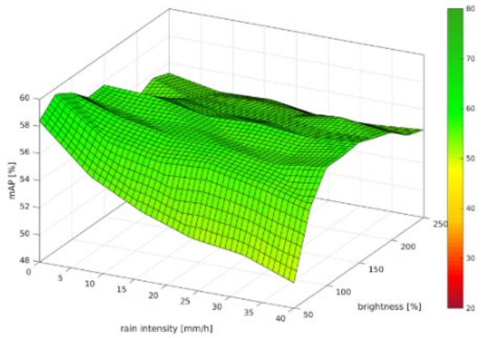

KITTI raw – 2D
0,80
0,70
0,60
0,50
0,40
0,30
0,20
0,10
0,00
YOLOv3
RRC
Faster-RCNN
Mean average precision
Safety score

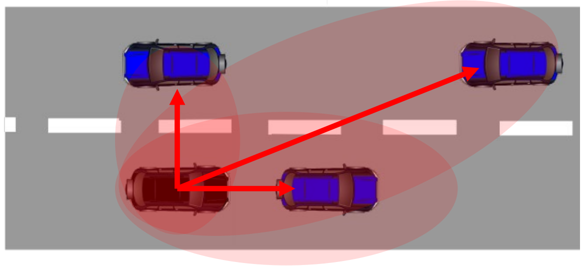

KITTI raw – 3D & Tracking
0,70
0,60
0,50
0,40
0,30
0,20
0,10
0,00
Mean average precision
MODA
MODP
MOTA
Safety score



Simulation – Perception Pipeline

Optimization – Local & Collective





Evaluation – Safety Metric

Literature

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Thank you.

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