Collaborative Approach to Sensor Perception Modelling (SENSI)

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Problem and Purpose

(two years project, now we are halfway)

Automated driving systems (ADS) rely on perception pipelines that are exposed to multiple sources of uncertainty: sensor limitations, environmental degradation, noise and error in human-generated labels, and perception model errors. Most simulation and evaluation frameworks still assume ideal perception, which creates a mismatch between virtual assessments and real-world performance. The SENSI project develops an open, data-driven stochastic perception model that captures these uncertainties.

Research Questions

- How can realistic perception uncertainty be estimated from heterogeneous datasets in which both human labels and model predictions contain error and noise?
- How can such uncertainty models be integrated into simulation and control so that ADS behavior adapts to varying perception reliability?

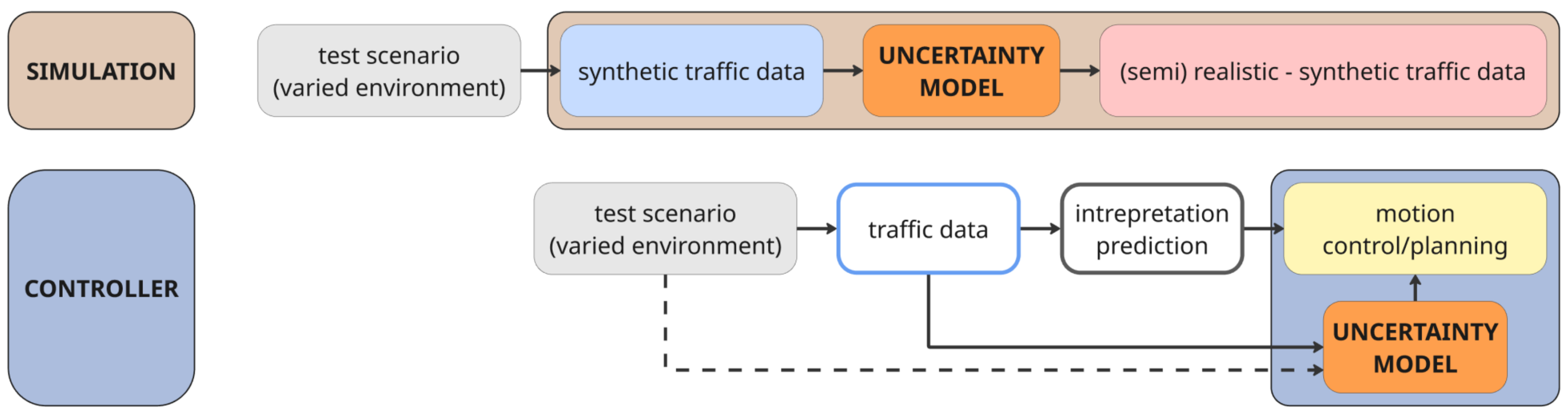

Figure 1: Uncertainty model integration in simulation and control pipelines.

Realization

Construction of the uncertainty model begins with an analysis of **various multimodal (automated driving) sensor datasets** selected to cover diverse **environmental conditions**, **sensor modalities**, and **object categories**. Because the datasets and ground truth are inherently incomplete and imperfect, the methodology relies on a **structured perception error taxonomy** that includes:

- sensor/environment errors
- ground-truth (human-label) errors
- perception-model (auto-label) errors
- dataset/domain limitations.

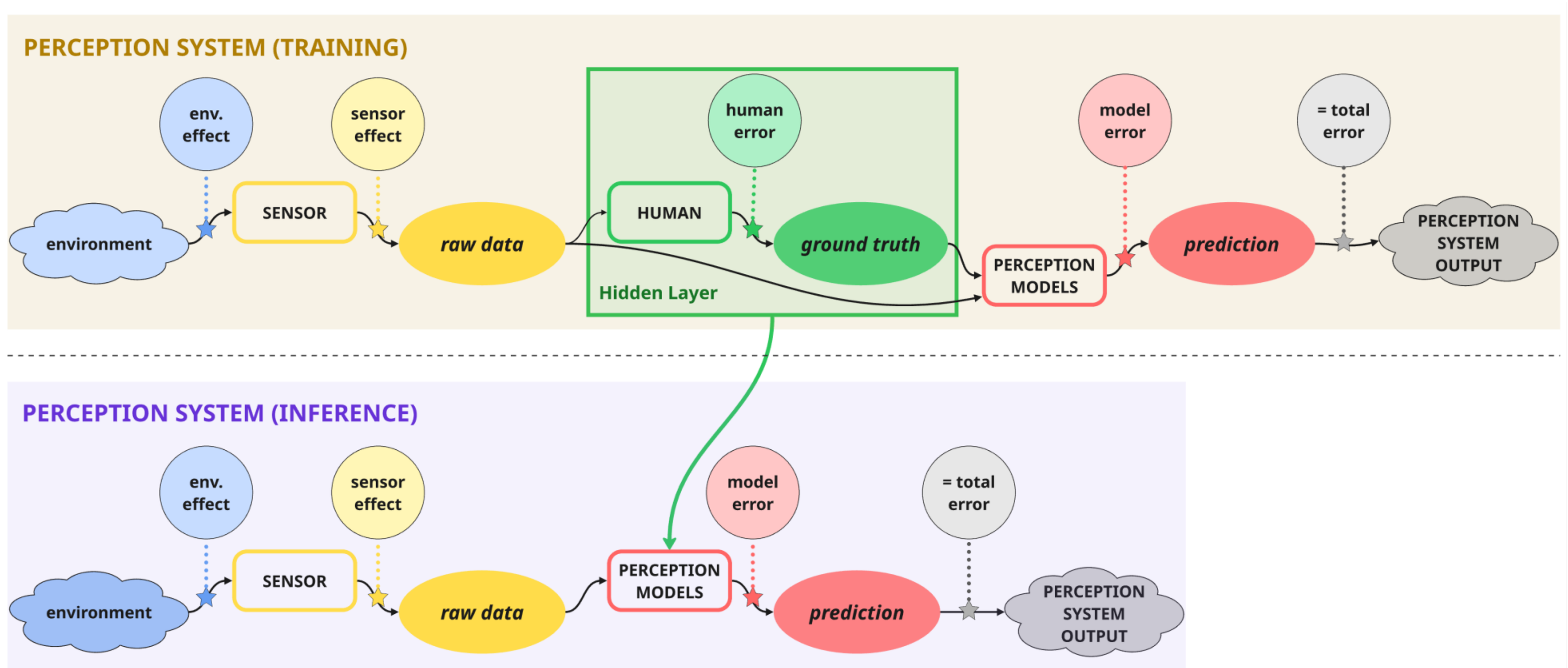

Figure 2: Perception system pipeline with error flow in training and inference.

Using this taxonomy, the uncertainty model learns how perception performance varies with **environment**, **object class**, and **object kinematics**. A consistent set of metrics is computed from both **ground truth** and **auto-label predictions**, enabling parallel characterization of annotation noise and model behavior.

The model outputs five uncertainty dimensions:

- detection probability
- temporal consistency error
- classification error
- localization error
- spatial error.

Together, these components form a **probabilistic uncertainty model** that quantifies how perception reliability changes across environmental conditions, object types, and motion states throughout the surrounding space of the ego vehicle.

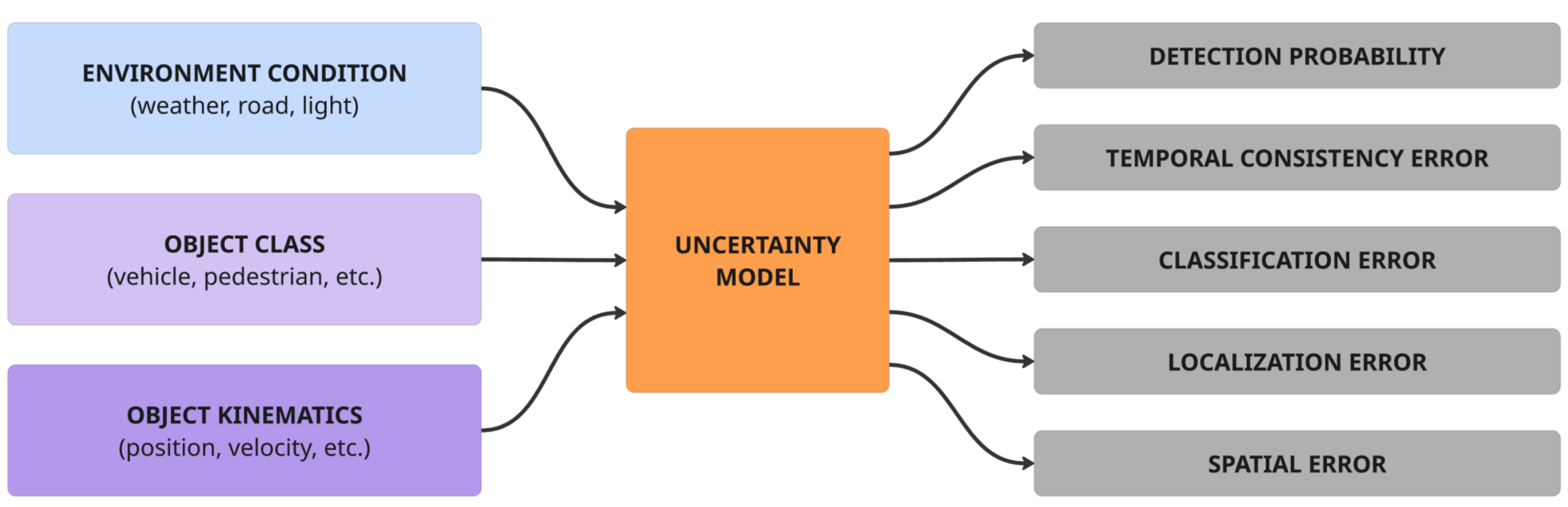

Figure 3: Uncertainty model's inputs and outputs.

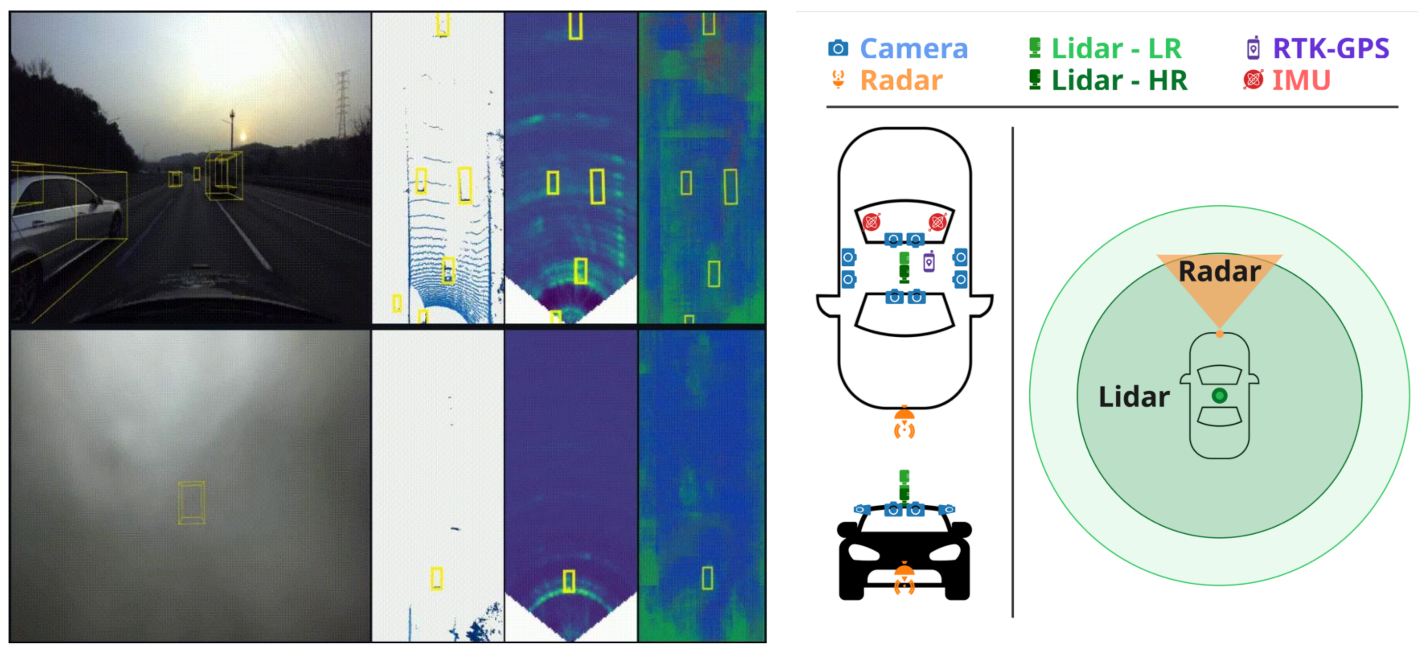

Figure 4: Kradar dataset (sample data quality, sensor types, and coverage ranges).

Results

Progress achieved so far includes the review of **various autonomous-driving datasets** and the selection of **KRadar** for the initial modelling phase, the development of a **hierarchical perception-error taxonomy**, the implementation of **robust label-quality metrics**, and the computation of **temporal, spatial, and semantic perception-error metrics** for both ground truth (human-labeled) and perception-model (auto-labels). These analyses have revealed distinct **environment-dependent uncertainty patterns** across weather conditions, road types, lighting, and object classes, establishing the empirical basis for constructing the probabilistic uncertainty model. Initial versions of the stochastic model are currently under development, along with an uncertainty-aware trajectory controller.

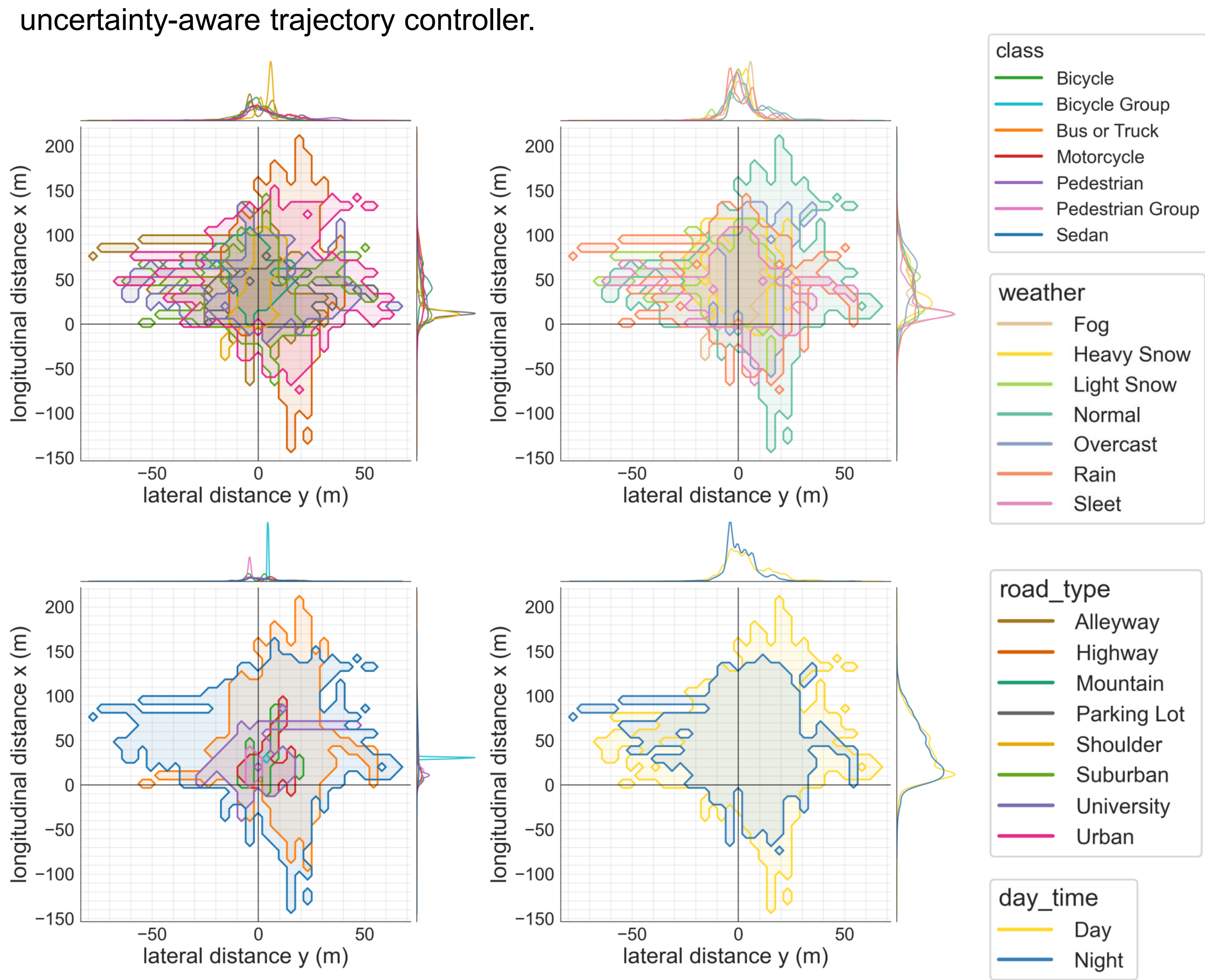

Figure 5: Spatial distribution and detection ranges in the ground-truth data.

Future work

Completion and validation of the full probabilistic uncertainty model

- Integration of causal inference to estimate uncertainty in underrepresented or unseen environmental conditions
- Evaluation of uncertainty-aware planning in closed-loop simulations
- Expansion of auto-label datasets to characterize model-induced uncertainty
- Release of open-source tools, metrics, and documentation as the model matures.

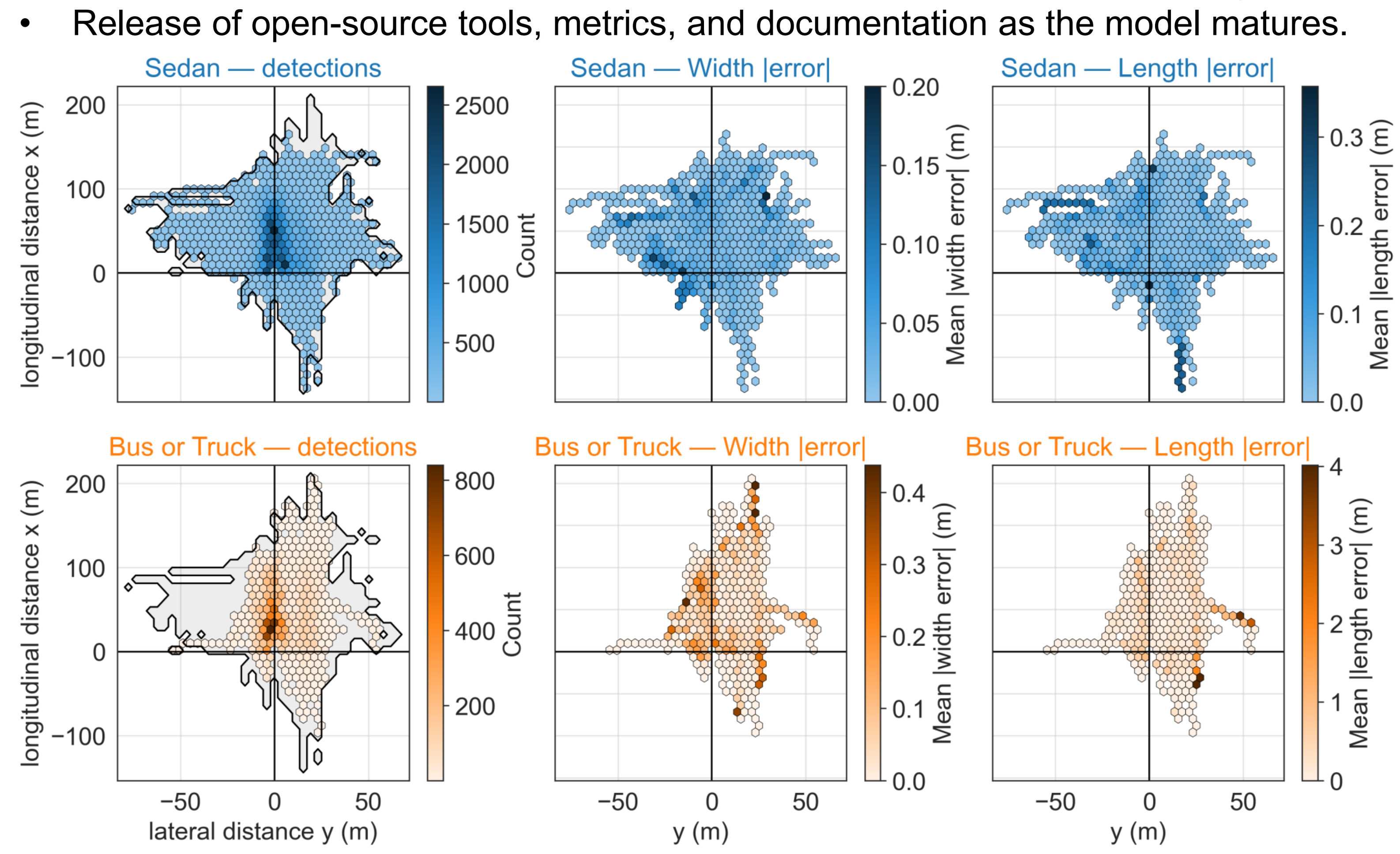

Figure 6: Mean spatial error (i.e., width and length) and their distribution in ground truth.

References

D.-H. Paek, S.-H. Kong and K. T. Wijaya, "K-Radar: 4D Radar Object Detection Dataset and Benchmark for Autonomous Driving in Various Weather Conditions," arXiv preprint arXiv:2206.08171, 2022.

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