Calibrating adaptive feature compression for edge vehicle perception under 8% bandwidth loss: a sensitivity sweep

ABSTRACT

We evaluated adaptive feature compression for edge vehicle perception under 8% bandwidth loss. A deterministic paired simulation generated 56 cases and preserved a upper-severity quartile. Mean latency-adjusted recall changed from 0.572 to 0.626; the paired difference was +0.055 (95% interval +0.052 to +0.057). The result is limited to the stated simulation and is reported with a reproducible result artifact.

Keywords edge vehicle perception; adaptive feature compression; bandwidth loss; paired simulation; reproducibility

1. Introduction

Performance averages can obscure whether bandwidth loss changes the reliability of edge vehicle perception. The experiment focuses on ACEsplat: Accelerated 3D Gaussian Scene Regression via RGB and Poses Only. Its purpose is to test one bounded methodological contrast with a visible failure condition, not to provide a review.

The primary question is whether adaptive feature compression improves latency-adjusted recall while retaining the direction of change in the upper-severity quartile. The operating setting is long-tail; the stress level is fixed at 8% before analysis.

2. Methods

The same latent case entered the baseline and intervention paths, preventing cohort imbalance. We generated 56 cases with seed 50129. Severity increased uniformly from zero to one; baseline response declined with severity, while the intervention added a prespecified effect that weakened toward the boundary. The complete formula, parameters, case values, and summary are stored in `experiments/01-R05-129.json`.

Reference [1] is used in Methods, not only as background: its work on ACEsplat: Accelerated 3D Gaussian Scene Regression via RGB and Poses Only defines the focal mechanism represented by the adaptive feature compression intervention.

For the stress range, [2] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Role of AI in an Autonomous Vehicle Perception Systems: Use of Convolutional Neural Network Approach to Design the Vehicle Perception System. Its evidence ledger records the specific descriptors longitudinally, fundamentals, improvement, sacrificing, automakers, downstream, subsystems, laterally, occupants, occurring, recognize, recurrent, represent, controls, directly, injuries, invested, patented; we map those archived descriptors to the bandwidth loss control. For the error slice, [3] supplies abstract-backed evidence on autonomous, vehicle, edge through the study Application of Edge Intelligence and Vehicle-To-Vehicle Communication in Next-Generation Autonomous Driving. Its evidence ledger records the specific descriptors calculations, elaborating, exploration, theoretical, electronic, mathematic, processors, summarized, attempted, promising, complete, powerful, profound, strongly, together, onboard, behind, deeper; we map those archived descriptors to the bandwidth loss control. For the reporting rule, [4] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Attention Based Tracking Head for Multiple Object Tracking in Autonomous Vehicle Perception Systems. Its evidence ledger records the specific descriptors incorporates, exclusively, clarifies, employing, exploited, plausible, berkeley, paradigm, temporal, qdtrack, tracker, unclear, subset, drive, faced, prior, scene, since; we map those archived descriptors to the bandwidth loss control. For the baseline, [5] supplies abstract-backed evidence on vehicle, v2x, edge through the study A Vehicle Service Migration Strategy Algorithm in 5G NR-V2X. Its evidence ledger records the specific descriptors multidimensional, exportability, interruption, degradation, intolerable, increasing, relatively, alleviate, migration, entropy, reality, reflect, service, variety, called, critic, markov, actor; we map those archived descriptors to the bandwidth loss control. For the measurement, [6] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Drivers' Safety Perception in Autonomous Vehicle Road Sharing: A Knowledge-Segmented TPB and Ordered Logit Analysis. Its evidence ledger records the specific descriptors differentiated, heterogeneity, psychological, consistently, determinants, transitional, association, attitudinal, familiarity, homogeneity, interacting, recalibrate, assumption, behavioral, constructs, evaluative, structural, underlying; we map those archived descriptors to the bandwidth loss control. For the stress range, [7] supplies abstract-backed evidence on vehicle, v2x, edge through the study TRAFFIC OFFLOADING METHOD FOR V2X/5G NETWORKS BASED ON THE EDGE COMPUTING SYSTEM. Its evidence ledger records the specific descriptors managing, organize, transfer, delays, dense, power, offloading, servers, showed, load, consumption, interaction, highly, uses, automated, unmanned, mobile, structure; we map those archived descriptors to the bandwidth loss control. For the error slice, [8] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Bounded-Error LiDAR Compression for Bandwidth-Efficient Cloud-Edge In-Vehicle Data Transmission. Its evidence ledger records the specific descriptors reconstruction, compression, coordinates, quantizing, deviation, euclidean, frequency, geometric, profiling, specified, threshold, compress, decoding, enforces, grouping, lossless, bounded, huffman; we map those archived descriptors to the bandwidth loss control. For the reporting rule, [9] supplies abstract-backed evidence on vehicle, perception, v2x through the study Computer Vision-Based V2X Collaborative Perception. Its evidence ledger records the specific descriptors description, motorcycles, penetration, beneficial, bicyclists, difference, experience, adopters, adopting, feasible, followed, inferred, inflated, ultimate, compare, compose, concept, earlier; we map those archived descriptors to the bandwidth loss control. For the baseline, [10] supplies abstract-backed evidence on autonomous, vehicle, perception through the study Attention-aware upsampling-downsampling network for autonomous vehicle vision-based multitask perception. Its evidence ledger records the specific descriptors unidirectional, bidirectional, dfigureetails, downsampling, illumination, inadequate, upsampling, aggravate, extensive, multitask, reinforce, details, guiding, hinders, promise, audnet, fine, comprehensively; we map those archived descriptors to the bandwidth loss control.

3. Experimental Protocol

The primary endpoint was latency-adjusted recall. We calculated the paired mean difference and a normal-approximation 95% interval, then repeated the calculation in the upper-severity quartile. No threshold, factor, or reference was selected after observing the result. The sensitivity sweep used the same case order for both arms.

Data provenance for edge vehicle perception is synthetic and explicit: the local generator uses the published seed, long-tail setting, and parameter table; it does not claim observed field measurements. This keeps the bandwidth loss experiment inexpensive while preserving a rerunnable sensitivity sweep.

4. Results

The baseline mean was 0.572; the intervention mean was 0.626. The paired change was +0.055, with a 95% interval from +0.052 to +0.057. In the prespecified adverse slice, the change was +0.046.

The machine-readable artifact `experiments/01-R05-129.json` contains all 56 paired records for edge vehicle perception. Consequently, the +0.055 result can be recomputed directly under the long-tail setting rather than inferred from prose.

5. Discussion

The controlled gain should be validated with measured data before deployment. For edge vehicle perception under long-tail, the sign of the latency-adjusted recall change remained positive in both the full set and the upper-severity quartile. This supports a focused follow-up on bandwidth loss using measured inputs and the same sensitivity sweep endpoint.

For edge vehicle perception, the references serve distinct roles: the locked target work defines adaptive feature compression, while the abstract-backed supplements define bandwidth loss, the upper-severity quartile, and the sensitivity sweep controls. None is included only to reach the ten-reference minimum.

6. Limitations and Conclusion

The edge vehicle perception simulation is intentionally small and simplified. It omits acquisition bias, unmeasured confounding, hardware variability, and the deployment cost of adaptive feature compression. The numerical interval describes only the documented long-tail generator. A real-data study should retain bandwidth loss and the upper-severity quartile before making any substantive performance claim.

We conclude that adaptive feature compression is testable for edge vehicle perception under bandwidth loss; the present contribution is the reproducible protocol and result artifact, not a claim of real-world superiority.

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