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SPEAR: Semantic Push and Evidence-Driven Adaptive Retrieval for V2I Collaborative Perception

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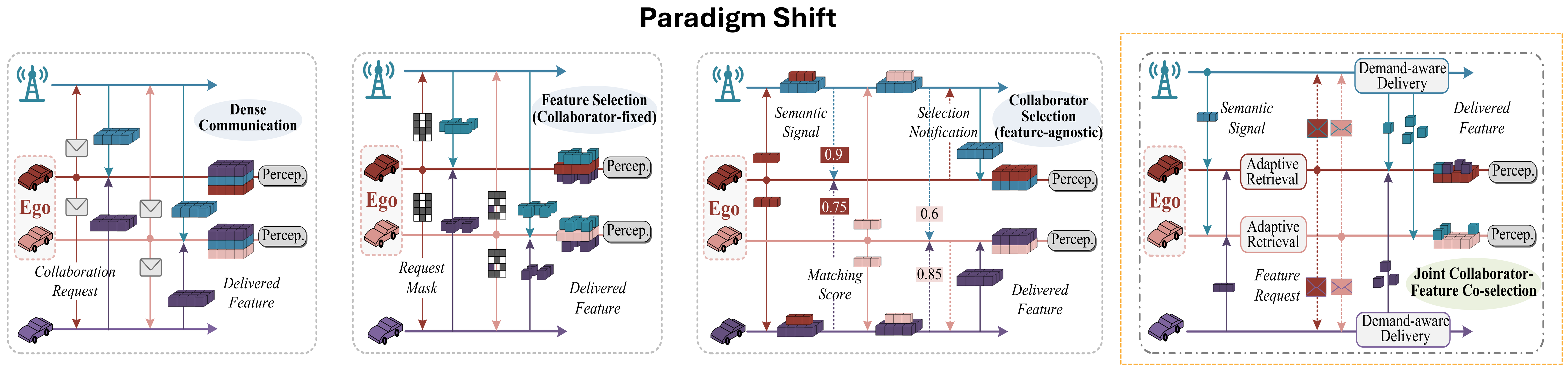
SPEAR replaces repeated ego-triggered handshakes with a single RSU semantic broadcast, enabling demand-aware feature retrieval for multiple egos.

Why SPEAR?

- Conventional collaborative perception relies on ego-triggered request–response interactions.
- Per-ego handshakes introduce growing signaling, computation, and contention overhead.
- Conventional confidence scores can be overconfident and fail to quantify the actual information gain provided by remote observations.

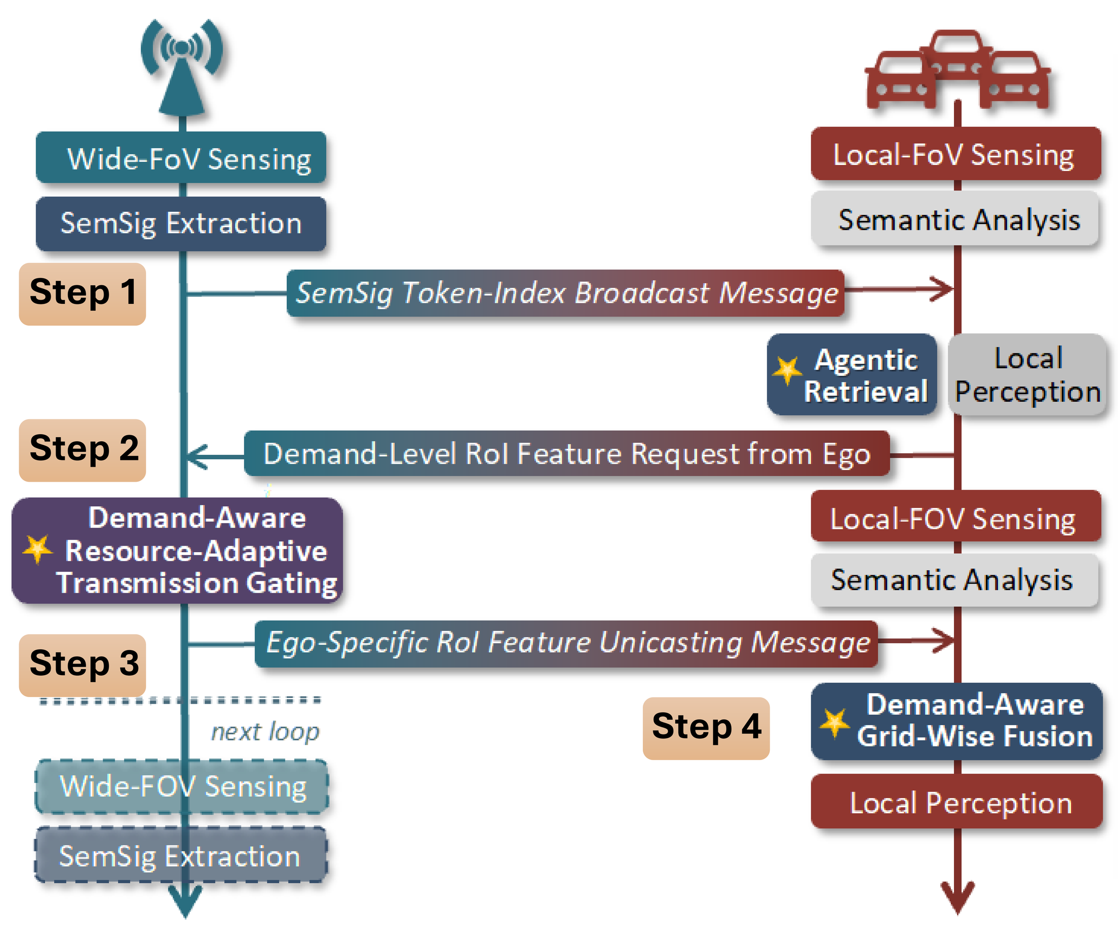
Confidence alone ≠ Reliable information gain

Paradigm Shift



From repeated ego-triggered querying to collaborator-initiated semantic push.

SPEAR Workflow



Broadcast globally · Evaluate locally · Retrieve selectively

Step 1: Semantic Broadcast

The RSU broadcasts a compact SemSig to all egos.

Step 2: Request Generation

Each ego identifies grids with high entropy gain.

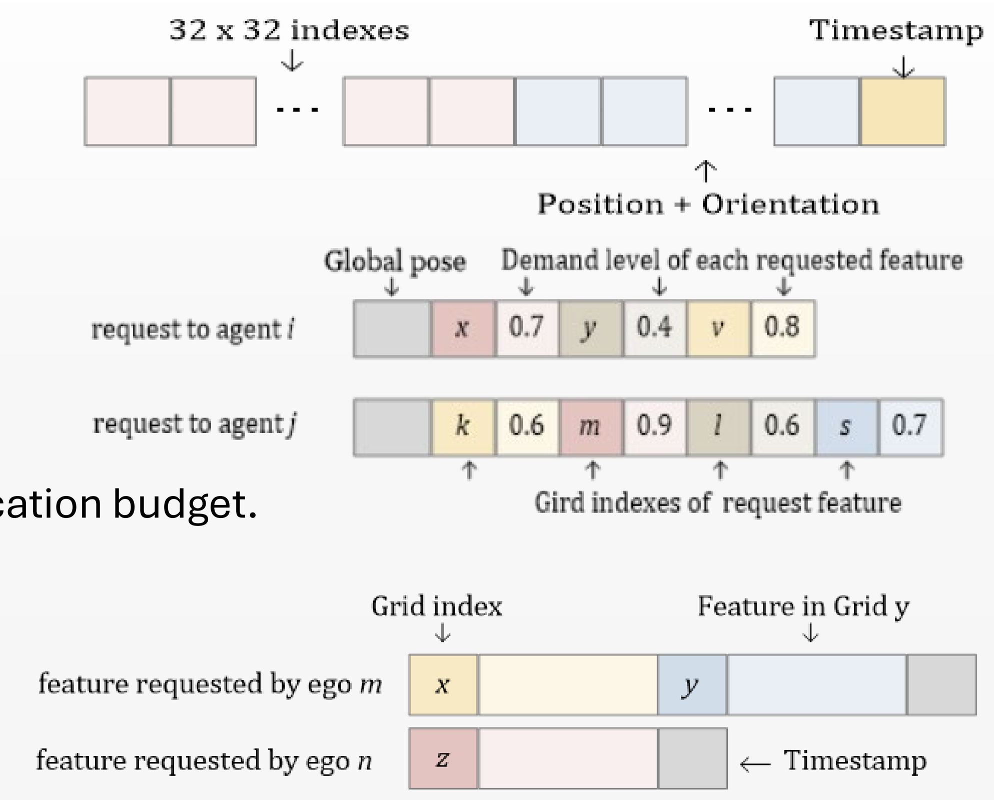
Step 3: Adaptive Response

The RSU transmits the requested features under the communication budget.

Step 4: Semantic Aggregation

Each ego performs reliability-aware grid-wise fusion.

Value + consistency + reliability

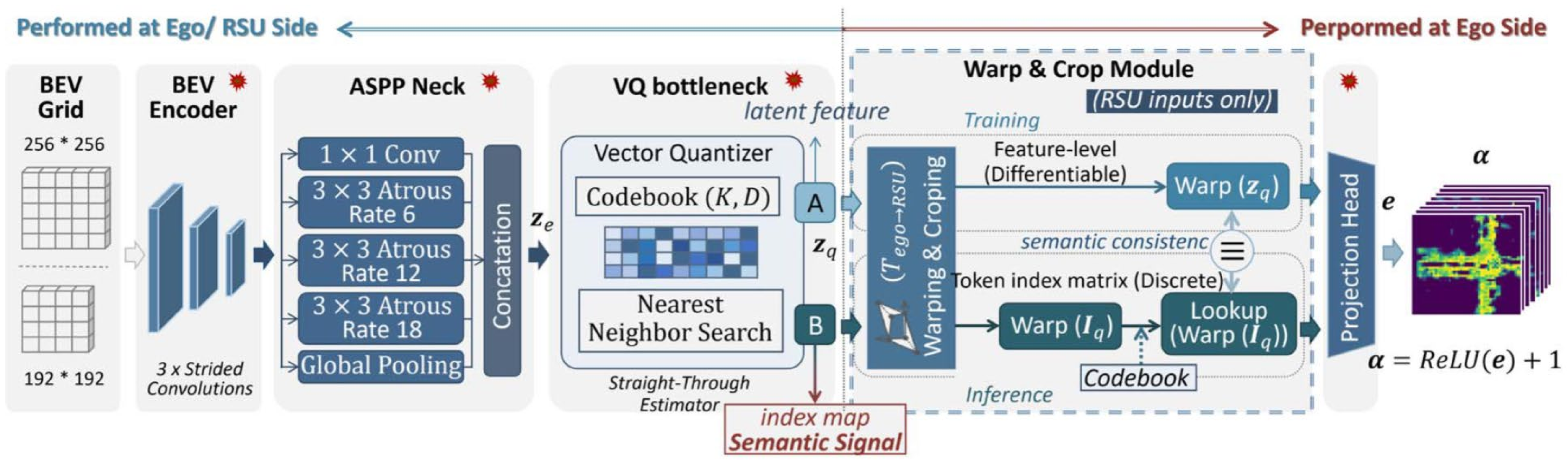


Contributions

✓ SemSig Extraction

BEV Encoder → ASPP → VQ Codebook → Discrete SemSig

- 32 × 32 semantic indices
- 444 active codewords
- ≈ 4.6 Kbits/frame



✓ Entropy-Gain-Driven Retrieval

Uncertainty-Guided Dirichlet Fusion

$$u_i^v = \frac{C}{S_i^v}, \quad u_i^{I\to v} = \frac{C}{S_i^{I\to v}},$$

$$w_i^v = 1-u_i^v \text{ and } w_i^{I\to v} = 1-u_i^{I\to v}$$

$$\alpha_i^{\text{fuse}} = \frac{w_i^v \alpha_i^v + w_i^{I\to v}\alpha_i^{I\to v}}{w_i^v + w_i^{I\to v}}.$$

$$\Delta\mathcal{H}_i = \mathcal{H}(\alpha_i^v) - \mathcal{H}(\alpha_i^{\text{fuse}}),$$

where $\mathcal{H}(\alpha_i)$ is the differential entropy of $\mathrm{Dir}(\alpha_i)$:

$$\mathcal{H}(\alpha_i) = \ln B(\alpha_i) + (S_i - K)\,\psi(S_i) - \sum_{k=1}^{K}(\alpha_{i,k}-1)\,\psi(\alpha_{i,k}),$$

ΔH_i measures how much the RSU observation is expected to reduce the ego's uncertainty at grid i.

The resulting entropy gain reflects the net utility of incorporating RSU observations rather than the raw disagreement between sources

✓ Reliability-Aware Grid-Wise Fusion

$$\tilde{g}_{v,n} = w_n g_{v,n} + (1-w_n)\, g_{I,n}$$

- Feature consistency
- Local evidence strength
- Entropy gain ΔH_n

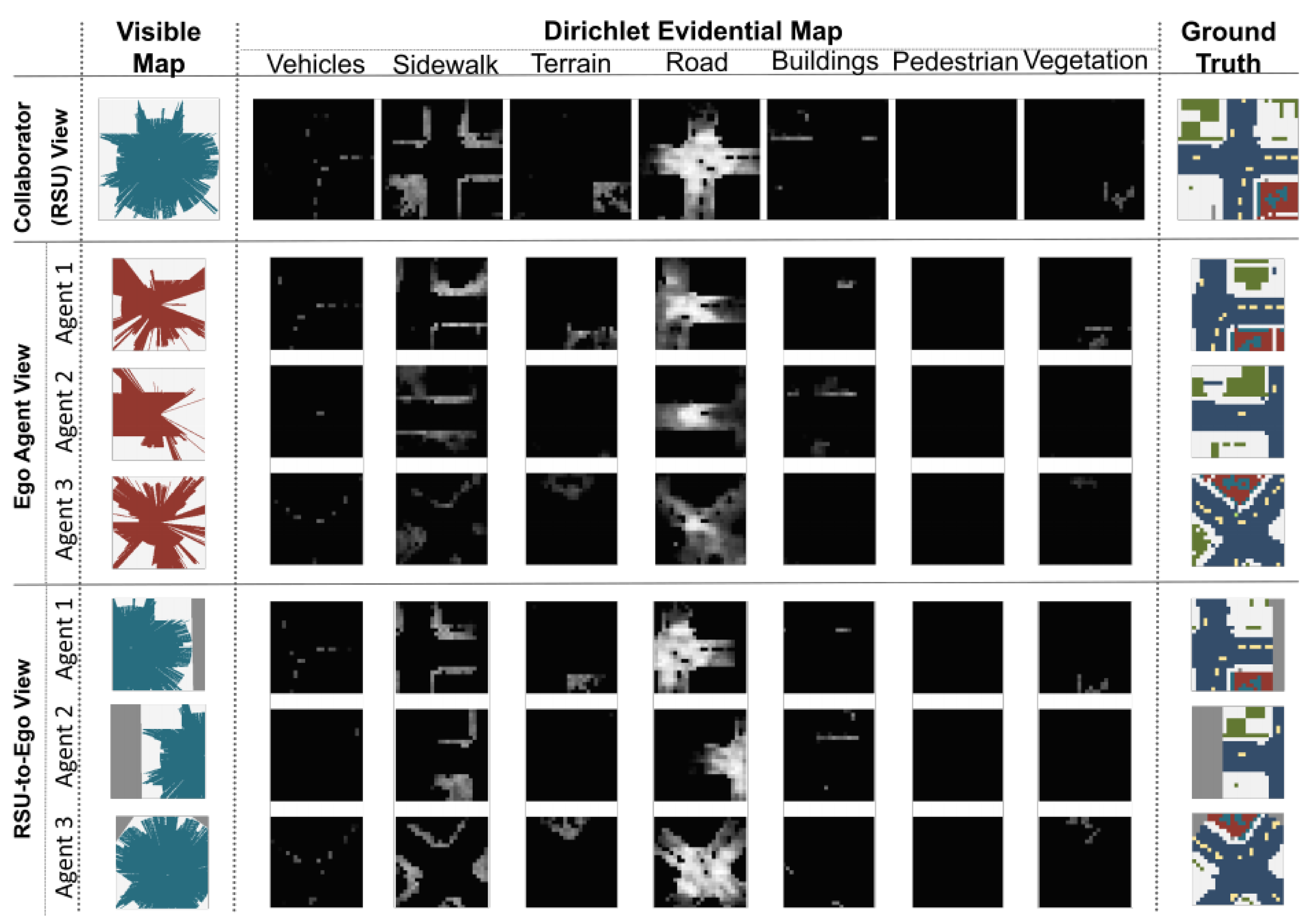
$$\mathbf{f}_n^{\text{cons}} = \left[\,|\mathbf{g}_{v,n}^v - \mathbf{g}_{v,n}^I|,\ \ \|\mathbf{g}_{v,n}^v\|_2,\ \ \|\mathbf{g}_{v,n}^I\|_2\,\right]$$

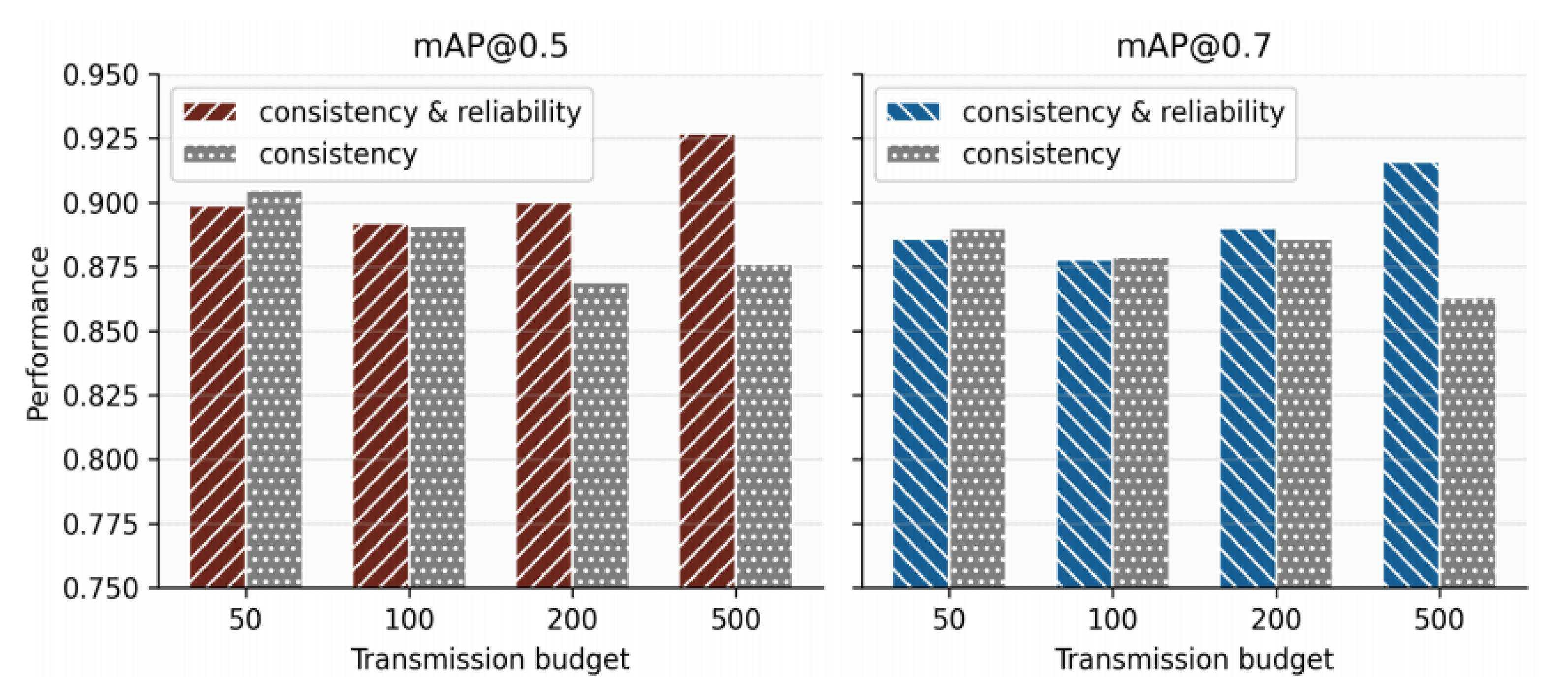
$$\mathbf{f}_n^{\text{rel}} = \left[\,\mathcal{H}(\alpha_n^v),\ \ \log(S_n^v+\epsilon),\ \ \Delta\mathcal{H}_n\,\right]$$

$$\mathbf{f}_n = \left[\,\mathbf{f}_n^{\text{cons}},\ \ \mathbf{f}_n^{\text{rel}}\,\right]$$

A lightweight MLP determines whether each grid should rely more on the local observation or the retrieved RSU feature.

Experimental Results





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