

Divide and Merge:

Motion and Semantic Learning in End-to-End Autonomous Driving

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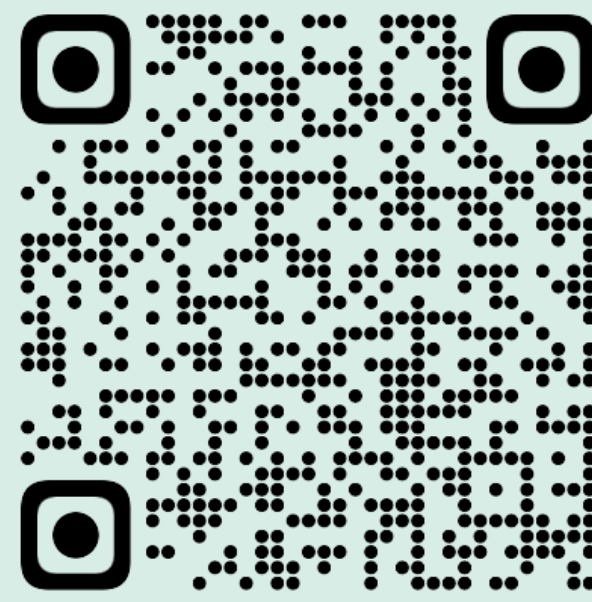
TLDR: solving the perception negative transfer problem boosts driving safety

The Problem: Current E2E models use a single feature vector to represent both **semantics** (what is it?) and **motion** (where is it going?). Forcing features to learn motion (prediction/planning) impairs their ability to represent semantics (detection/tracking). Perception performance drops when jointly trained with prediction and planning, which is known as **perception negative transfer**.

Our Solution (DMAD):

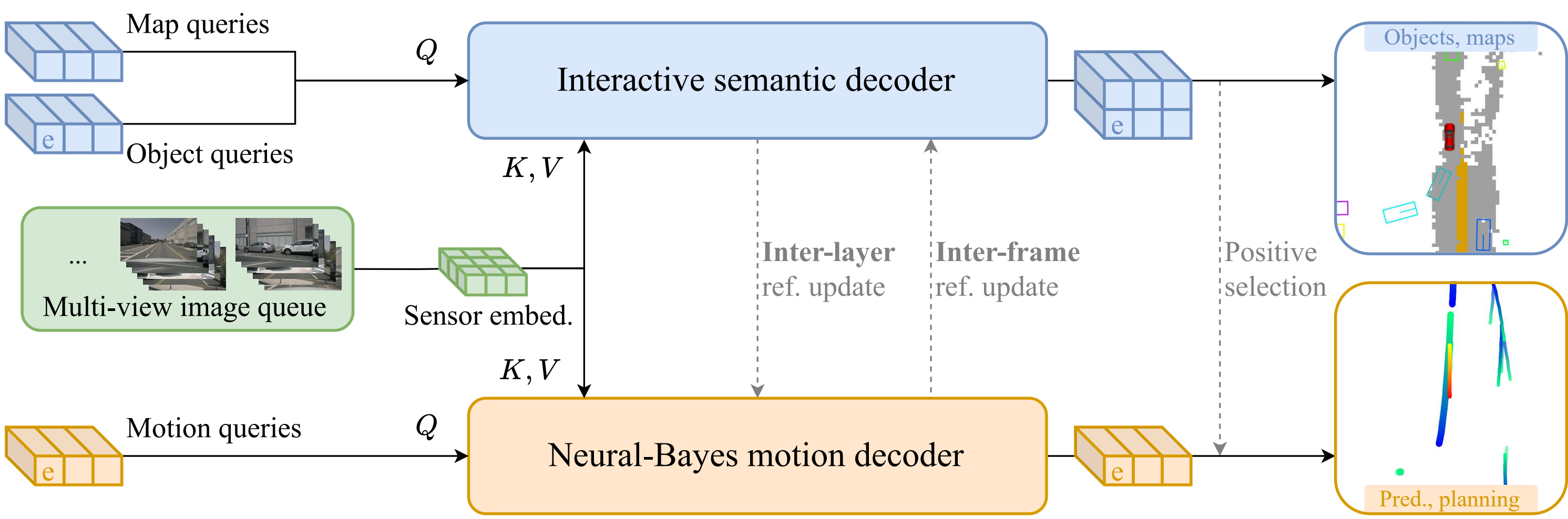
- **Divide:** Decouple heterogeneous tasks (motion vs. semantics) into parallel pathways, **mitigating negative** transfer.
- **Merge:** Enhance similar tasks (object vs. map) via interactive attention, **promoting positive** transfer.

Results: performance improvements across **all tasks** (object & map perception, prediction, and planning).



3-min video

Overview: the DMAD framework



Structure: Parallel semantic and motion learning in two pathways.

1. Divide: Neural-Bayes motion decoder

Goal: Decouple motion from semantics to stop negative transfer.

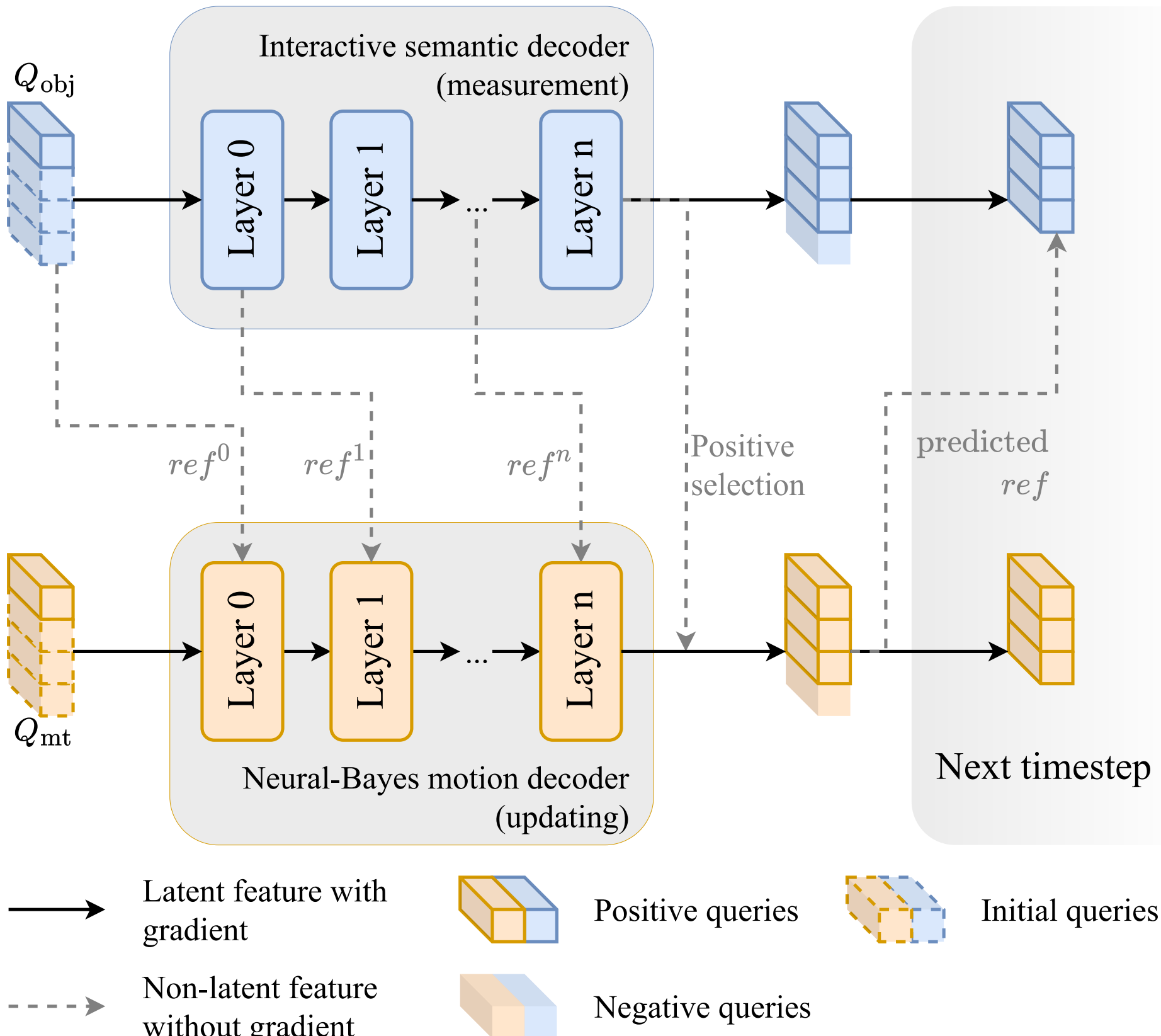
- **Object representation:** A query pair (Q_{mt} and Q_{obj}) represents an object instance.
- **Bayes filter inspiration:** Measurement, updating and prediction.
- **Recursive design:** Recursively exchanging reference points between both kinds of queries.

2. Merge: interactive semantic decoder

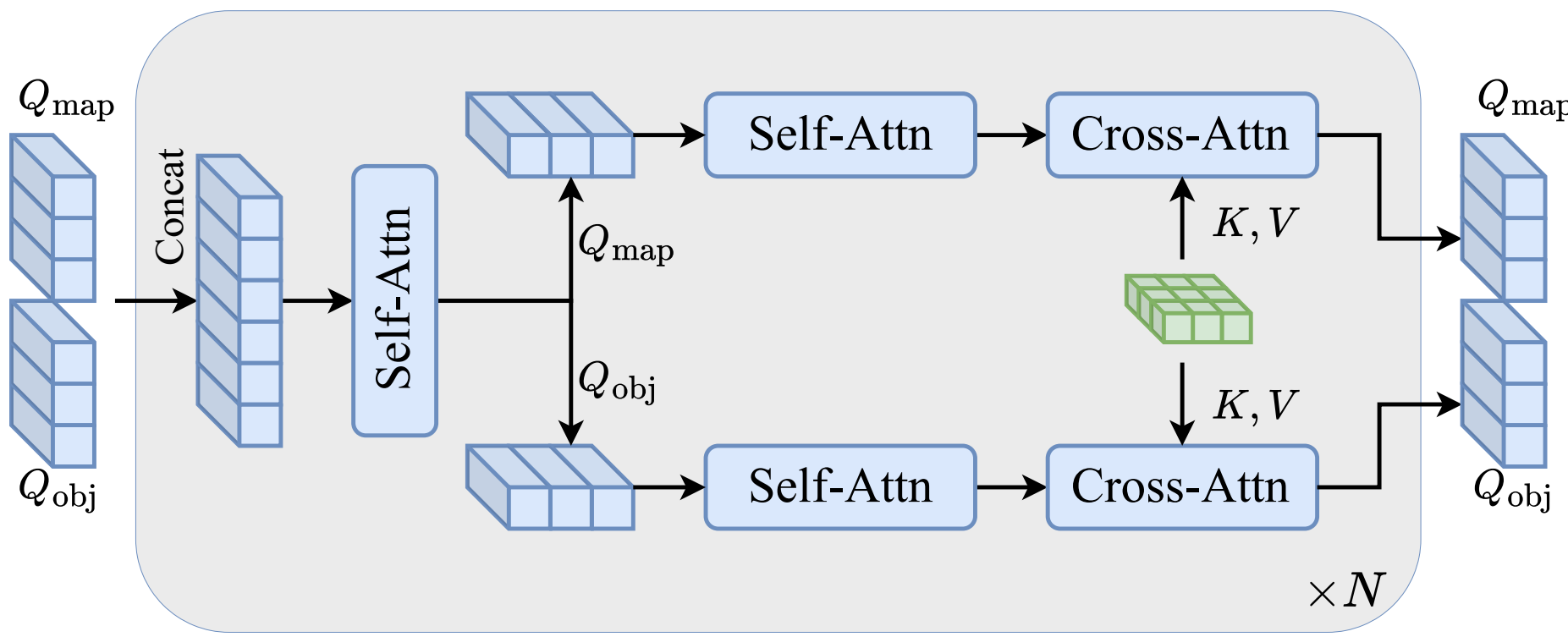
Goal: Enhance semantic consistency between objects and maps.

- **Intuition:** Cars are likely to be on drivable areas.
- **Mechanism:** A self-attention module allows Q_{obj} and Q_{map} to exchange context.

Module diagrams



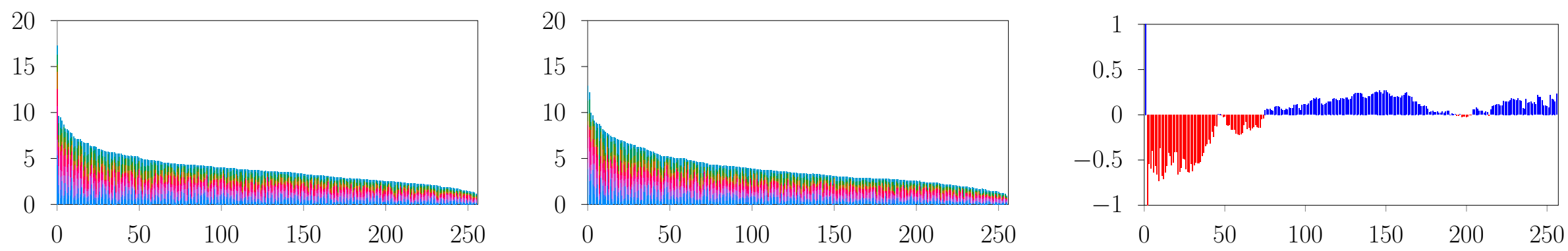
Divide: Neural-Bayes motion decoder



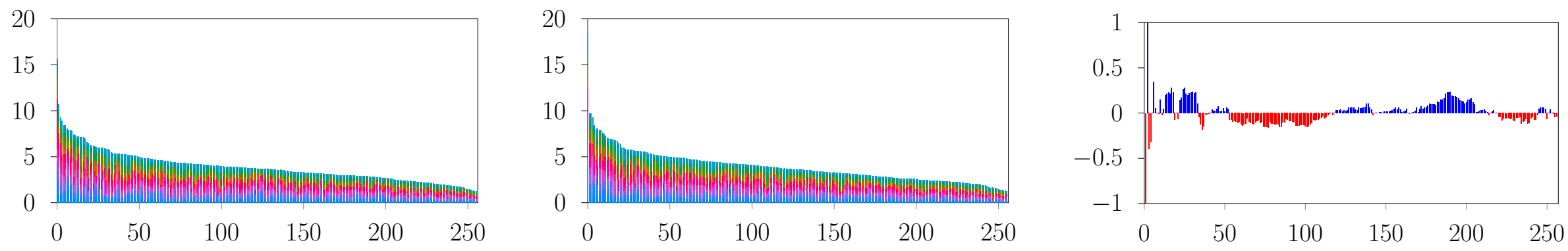
Merge: interactive semantic decoder

Visualizations

1. SHAP values analysis: DMAD maintains the SHAP values of the object query across two training stages, which **interprets the elimination of negative transfer**. From left to right: stage 1, stage 2, and the difference (stage 1 minus stage 2). In the difference diagram, **red** indicates a negative value and **blue** signifies a positive value.

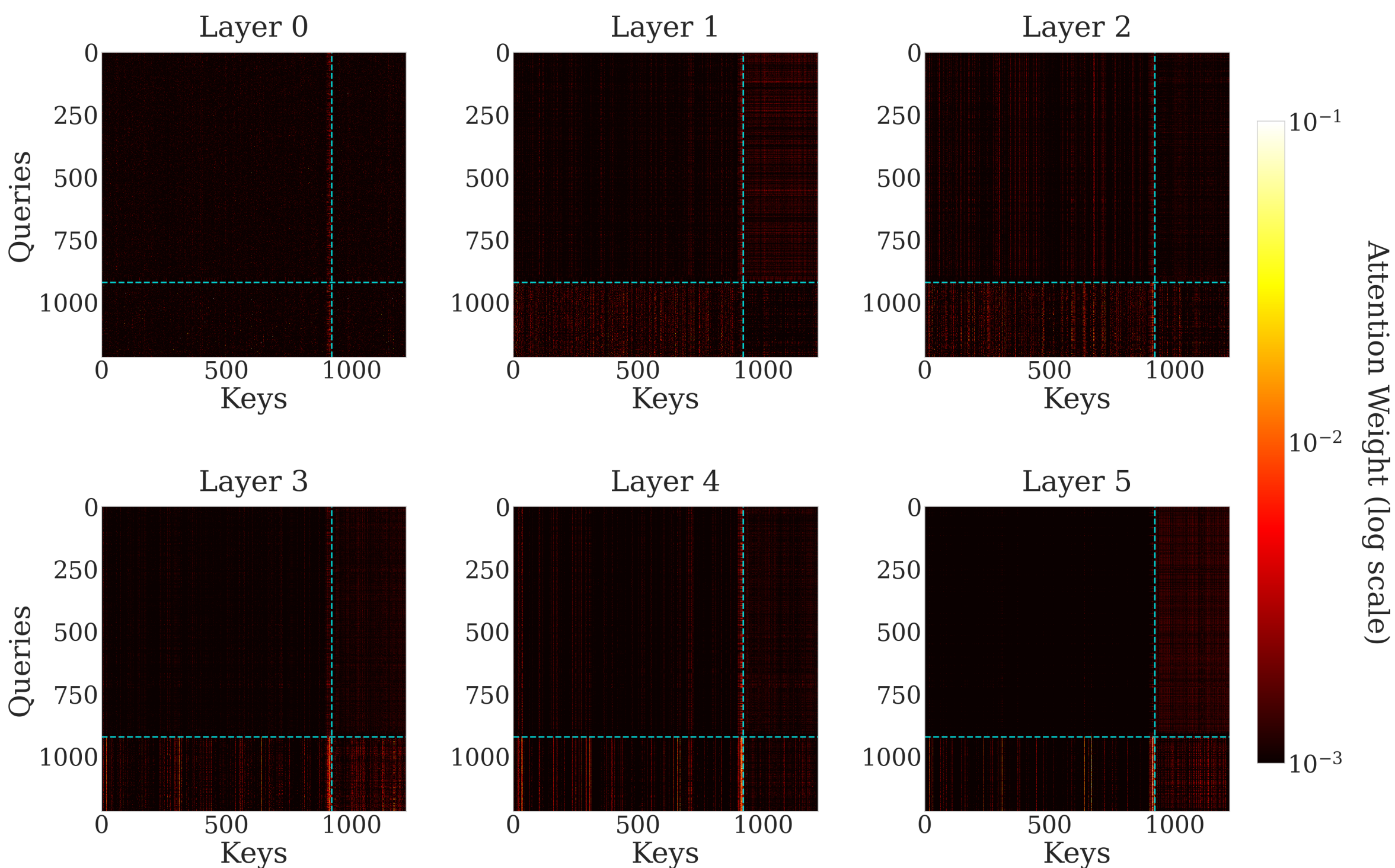


(a) SHAP values of UniAD.



(b) SHAP values of DMAD.

2. Object & map self-attention heatmaps: Cyan dashed lines divide a heatmap into four attention regions. **upper-left:** object to object; **upper-right** object to map; **lower-left:** map to object; **lower-right** map to map.



Applying “Divide and Merge” structure to UniAD and SparseDrive, resulting in **DMAD** and **SparseDMAD**.

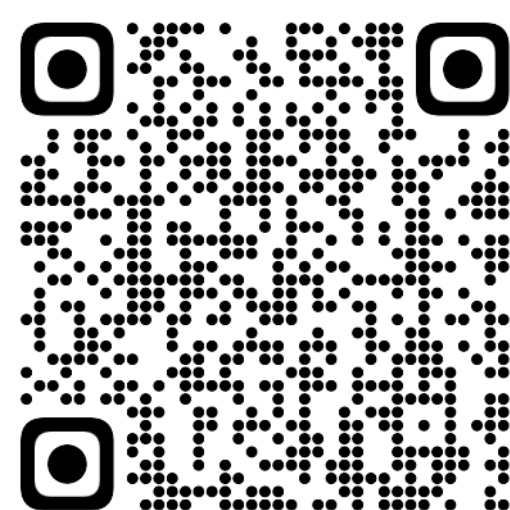
1. Mitigating Negative Transfer: Experiments on nuScenes benchmark show that our methods mitigate the negative transfer in training stage 2. Performance changes in stage 2 are shown in parentheses (**red**: decline, **blue**: improvement).

Method	NDS↑	mAP↑	AMOTA↑	AMOTP↓
UniAD - stage 1	0.497	0.382	0.374	1.31
UniAD - stage 2	0.491 (-1.2%)	0.377 (-1.3%)	0.354 (-5.3%)	1.34 (+2.3%)
DMAD - stage 1	0.504	0.395	0.394	1.32
DMAD - stage 2	0.506 (+0.4%)	0.396 (+0.3%)	0.393 (-0.3%)	1.30 (-1.5%)
SparseDrive - stage 1	0.531	0.419	0.395	1.25
SparseDrive - stage 2	0.523 (-1.5%)	0.417 (-0.5%)	0.376 (-4.8%)	1.26 (+0.8%)
SparseDMAD - stage 1	0.536	0.424	0.396	1.23
SparseDMAD - stage 2	0.534 (-0.4%)	0.427 (+0.7%)	0.395 (-0.3%)	1.23 (0%)

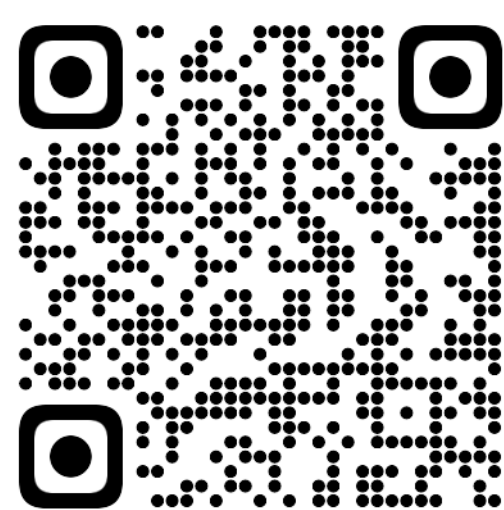
2. Closed-loop planning: Experiments on NeuroNCAP demonstrate that our advances in perception transform to planning safety.

Method	NeuroNCAP scores ↑				Collision rates (%) ↓			
	Stat.	Frontal	Side	Avg.	Stat.	Frontal	Side	Avg.
UniAD	3.50	1.17	1.67	2.11	32.4	77.6	71.2	60.4
DMAD	4.40	1.47	2.07	2.65	14.8	74.0	61.6	50.1
SparseDrive	4.42	2.96	2.30	3.23	22.4	62.8	60.4	48.5
SparseDMAD	4.57	3.14	2.42	3.37	18.4	60.0	59.1	45.8

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Code