

# Leveraging SD Map to Augment HD Map-based Trajectory Prediction

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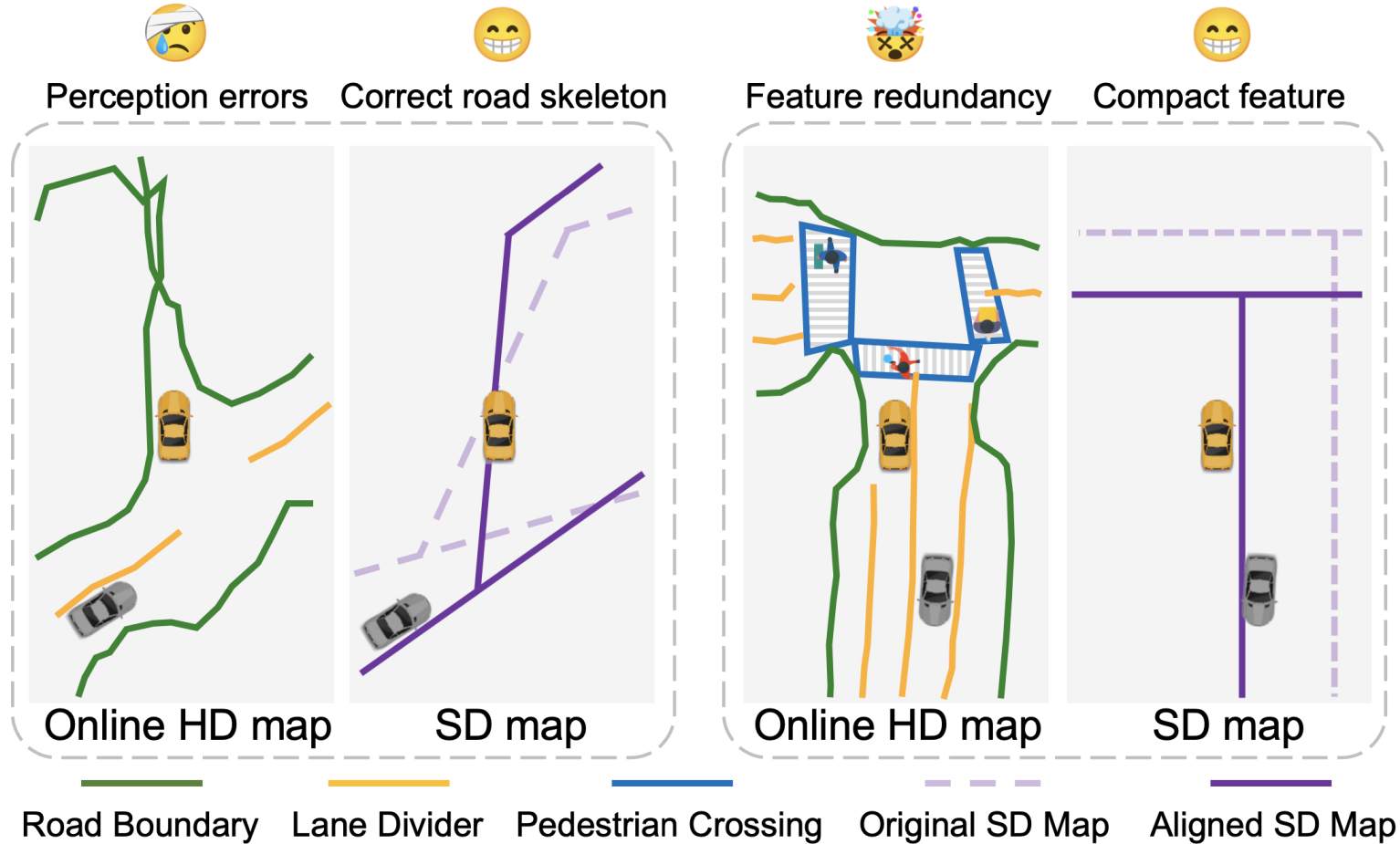
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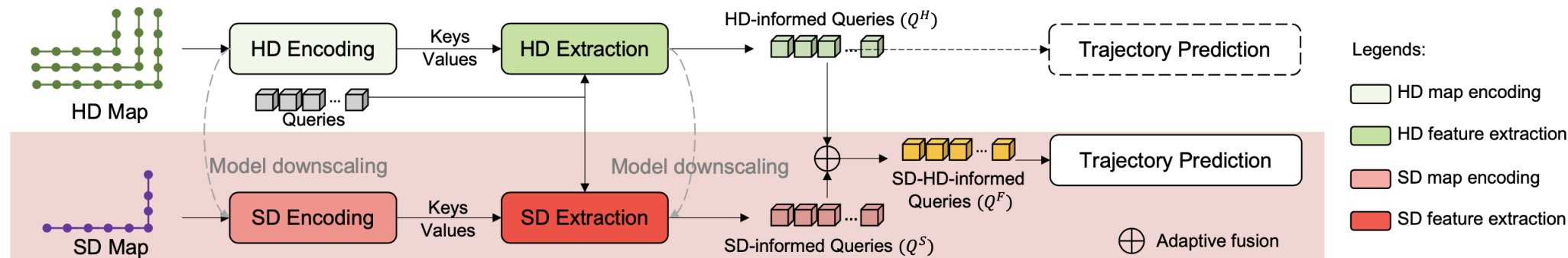
# Two problems of HD map-based trajectory prediction



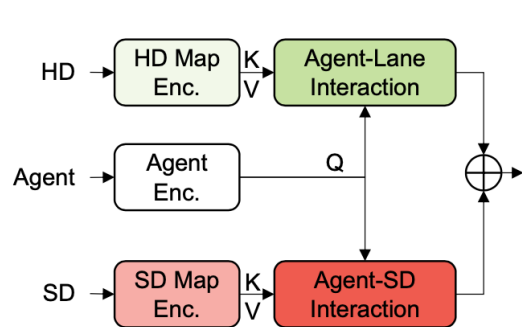
## Goal of the work:

Improve trajectory prediction performance in real-world autonomous driving scenarios that rely on online HD maps through **leveraging SD maps**.

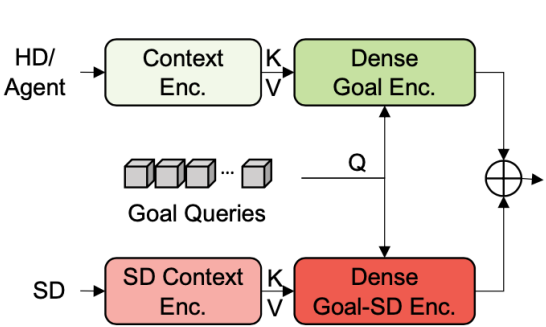
# A general SD-HD fusion framework



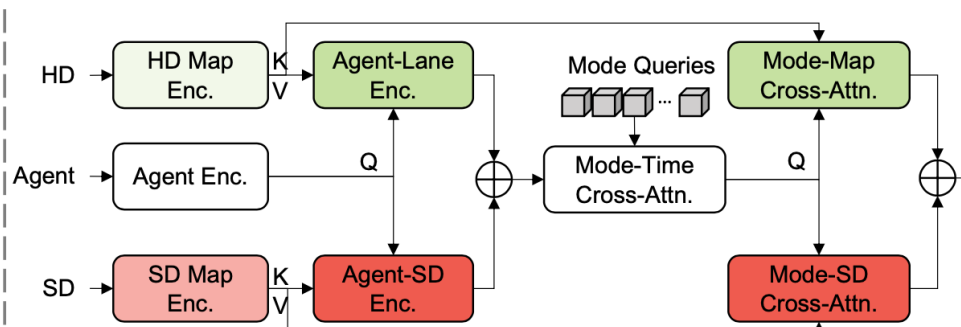
(a) SD-HD fusion framework



(b) HiVT with SD-HD fusion



(c) DenseTNT with SD-HD fusion

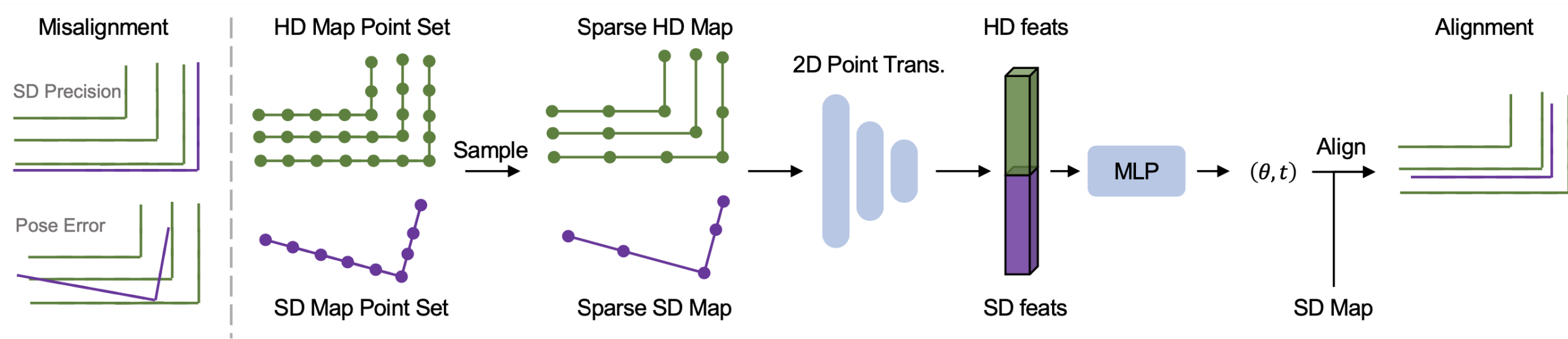


(d) QCNet with SD-HD fusion

## Fusion principle:

SD maps should be integrated into trajectory prediction in the same way that the baseline model utilizes HD maps.

# Solve the misalignment between SD and HD



**Motivation:** There is misalignment between SD and HD maps due to vehicle pose errors and map errors, so it is necessary to align them for better feature extraction.

## Key Designs:

- Extraction map topology features using 2D point transformer.
- Predict rotation and translation of SD map relative to HD map.

# Performance、ablation and efficiency experiments

Map Input		HiVT			DenseTNT			QCNet		
Method	mAP↑	ADE↓	FDE↓	MR↓	ADE↓	FDE↓	MR↓	ADE↓	FDE↓	MR↓
SD	N/A	0.454	0.89	0.107	1.379	2.255	0.444	0.401	0.871	0.091
MapTRv2	53.49	0.399	0.832	0.095	1.174	2.191	0.403	0.385	0.801	0.087
+ SATP	53.49	0.37	0.731	0.075	1.023	2.08	0.393	0.371	0.698	0.071
+ SATP + [8]	55.12	0.366	0.715	0.071	1.017	1.92	0.379	0.362	0.673	0.069
HRMapNet	74.16	0.397	0.82	0.091	0.907	1.671	0.218	0.371	0.796	0.083
+ SATP	74.16	0.365	0.722	0.071	0.732	1.406	0.183	0.358	0.637	0.062 (-25%)
+ SATP + [8]	74.91	0.362	0.72	0.07	0.709	1.397	0.181	0.346	0.625	0.062
GT HD	GT	0.371	0.736	0.072	0.852	1.475	0.199	0.36	0.632	0.062
GT HD + SATP	GT	0.336	0.672	0.065	0.724	1.388	0.175	0.327	0.615 (-3%)	0.06

Table 1. Performance of SATP on nuScenes. GT means ground-truth. A larger mAP means a better online HD map. We highlight the maximum (25%) and minimum (3%) improvements brought by SATP for combinations of different map inputs and baseline models.

Method	ADE↓	FDE↓	MR↓
HiVT + MapTRv2	0.399	0.832	0.095
+ SATP	<b>0.37</b>	<b>0.731</b>	<b>0.075</b>
+ SATP/without AlignNet	0.391	0.818	0.089
+ SATP/with CNN align	0.388	0.807	0.082
+ SATP/with SD→HD	0.393	0.81	0.093
+ SATP/with HD→SD	0.396	0.823	0.091

Table 3. Ablation study of SATP on HiVT.

Model	Param(M)↓	Latency(ms)↓
HiVT	2.6	36
HiVT + SATP	2.9 (+0.3M)	39 (+8%)
DenseTNT	1.6	317
DenseTNT + SATP	1.8 (+0.2M)	335 (+6%)
QCNet	7.7	142
QCNet + SATP	8.1 (+0.4M)	153 (+8%)

Table 4. Efficiency study of SATP.

# Conclusions

- We propose an **SD-HD fusion framework** to integrate SD maps into various HD map-based trajectory prediction models.
- We propose AlignNet to explicitly **align SD maps with HD maps**, enhancing the effectiveness of SD maps in augmenting HD map-based trajectory prediction.
- We **implement SATP on several representative trajectory prediction** models and improve their performance on real-world trajectory prediction benchmarks up to 25%.

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