

Motivation

Our goal is to produce plausible trajectories for motion forecasting by adhering to physical and environmental constraints. We propose a method that integrates explicit knowledge priors, ensuring predictions comply with vehicle kinematics and driving environment geometry. Our approach includes a nonparametric pruning layer and attention layers to incorporate these priors. This ensures reachability guarantees for traffic actors in various scenarios, leading to accurate and safe predictions vital for autonomous vehicle safety and efficiency. In essence, we present a method that prevents off-road predictions by embedding knowledge priors into the training process for reliable motion forecasting.

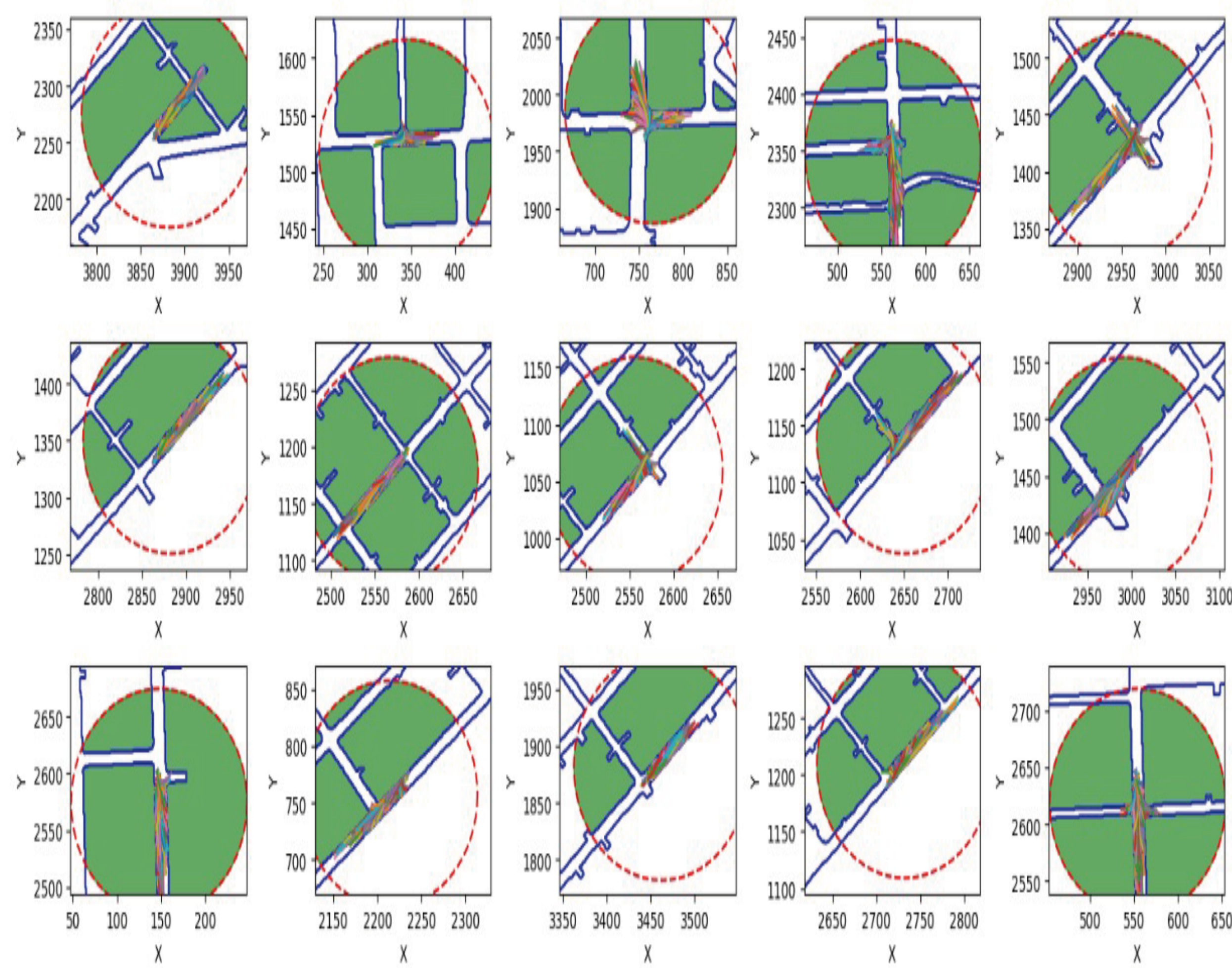


Figure 1: The green area delineates the local buffer polygon, non-drivable regions. The blue linear entities correspond to the lane boundaries. Subsequently, the peripheries of the green polygons undergo collision detection analysis to expedite pruning. (© FZI)

Objective

- Predict trajectories for an actor using the kinematic compliant trajectories that also respect the environmental boundaries.
- Trajectory sets contain kinematic motions which are then checked for collision with the green area as shown in Fig 1.

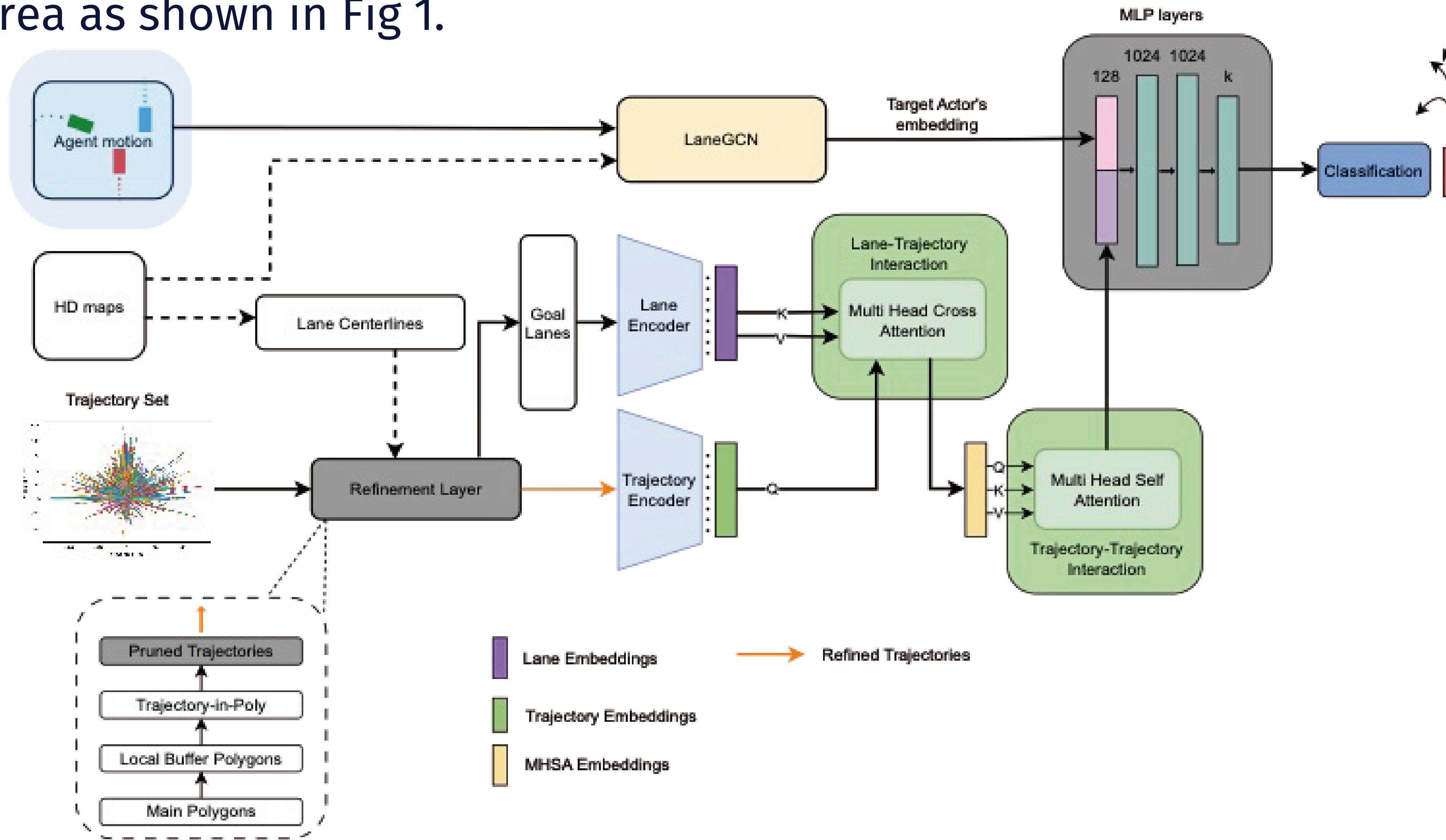


Figure 2: High-level overview of the architecture. The refinement layer takes two inputs. 1. Lane centerline points for a given query window and 2. trajectory sets with an $\epsilon = 2m$ coverage. The refinement layer produces feasible/pruned trajectories by constructing a lane boundary given the lane-centerline points. (© FZI)

Methodology

- Refinement layers produce trajectories by performing pruning on the trajectory set.
- Goal positions through lane centerlines are encoded via LSTM which represent the probable travel direction of an actor.
- Together with goal lanes and pruned trajectories we fuse both these information via transformer-based attention layers.
- Other actor's past observations are also encoded using LaneGCN[1] backbone which is then trained in an end-to-end manner with the rest of the network.
- Learning is done via maximum entropy where the loss function motivates the network to assign higher probabilities to feasible trajectories with a small distance to the ground truth trajectory.

Models	LowerBound		K=1			K=6			DAC
	minADE	minFDE	minADE	minFDE	MR	minADE	minFDE	MR	
Argo-NN+Map (prune)	Reg	Reg	3.38	7.62	0.86	1.68	3.19	0.52	0.94
Argo-NN	Reg	Reg	3.45	7.88	0.87	1.71	3.29	0.54	0.87
Argo-CV	Reg	Reg	3.53	7.89	0.83	-	-	-	0.88
WIMP [10]	Reg	Reg	1.43	6.37	-	1.07	1.61	0.23	-
LaneGCN [9]	Reg	Reg	1.71	3.78	0.67	0.90	1.77	0.26	-
Covernet $\epsilon = 2$ [8]	1.02	0.68	3.46	8.70	0.78	1.85	3.83	0.44	-
LaneGCN (Pre-trained)+Ours	1.02	0.68	1.97	4.72	0.73	1.55	2.04	0.25	0.99
LaneGCN (Full)+Ours	1.02	0.68	1.82	4.23	0.69	1.52	1.94	0.22	0.99

Figure 3: Quantitative comparison of different metrics on Argoverse validation split.

Results

Our primary objective is to prevent off-road predictions, which is reflected in our high Driving Area Compliance (DAC) score of 0.99. This score suggests that our method effectively excludes nearly all unfeasible states from the prediction space utilized by the network. This indicates that our approach effectively eliminates almost all infeasible reachable states from the prediction space used by the network.

References:

- [1] M. Liang et al., "Learning lane graph representations for motion forecasting," in Computer Vision – ECCV 2020

Partners



External partners



For more information contact:

Vivekanandan@fzi.de
Hubschneider@fzi.de

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