KI DELTA LEARNING
Scalable AI for Automated Driving

CRAT-Pred: Vehicle Trajectory Prediction with Crystal Graph Convolutional Neural Networks and Multi-Head Self-Attention

Julian Schmidt, Julian Jordan, Franz Gritschneder and Klaus Dietmayer

Knowledge Transfer

Trajectory Prediction Model (CRAT-Pred)

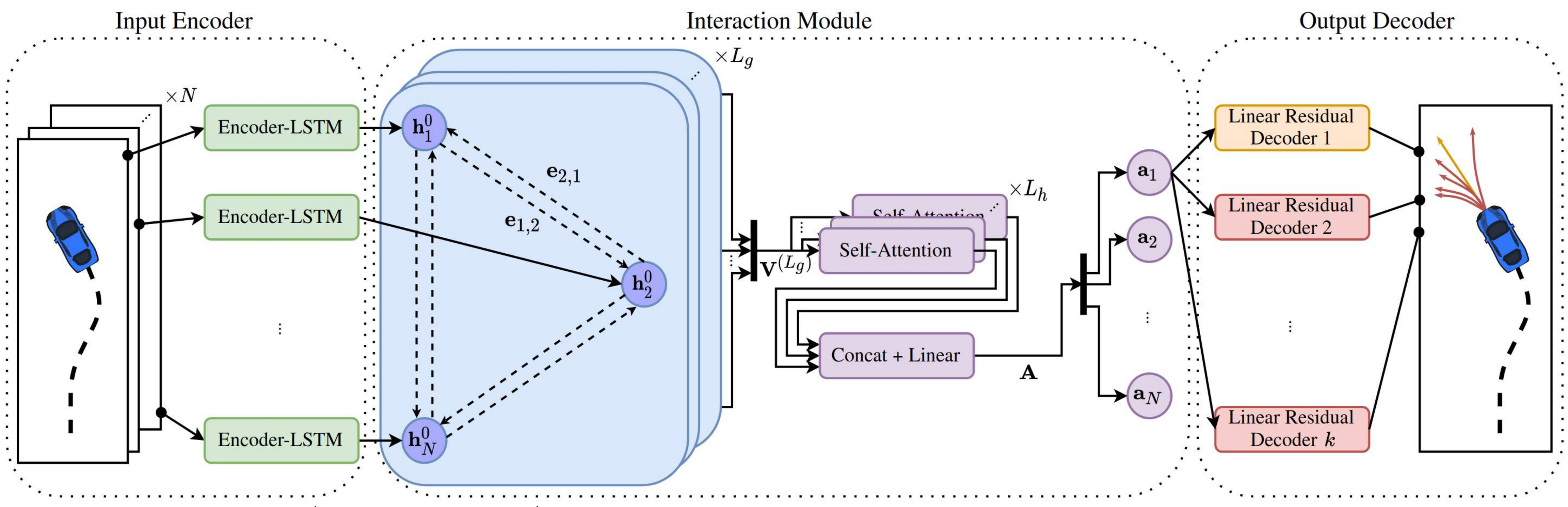

Figure 1: Model architecture (© Mercedes-Benz AG)

Objective

For safe autonomous driving, there is a strong need to predict the future motion of vehicles participating in traffic. The architectural design and the corresponding training process of most state-of-the-art models is designed for the incorporation of map information. With CRAT-Pred we propose a novel trajectory prediction method that achieves competitive results without relying on map data.

Main Contributions:

1) Novel map-free trajectory prediction model for vehicles
2) Extensive evaluation on the Argoverse Motion Forecasting Dataset [6] proves state-of-the-art performance with significantly less model parameters
3) Quantitatively show that self-attention is able to learn social interactions

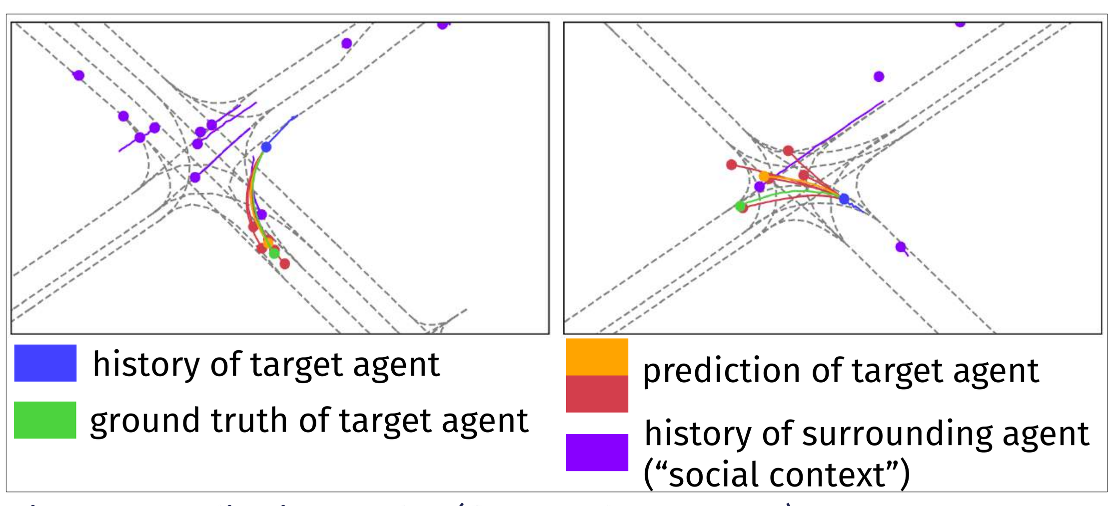

Figure 2: Qualitative results. (© Mercedes-Benz AG)

Method	$k=1$ minADE	$k=1$ minFDE	$k=1$ MR	$k=6$ minADE	$k=6$ minFDE	$k=6$ MR
LSTM ED [6]	2.15	4.97	0.75	-	-	-
LSTM ED-soc. [6]	2.15	4.95	0.75	-	-	-
NN [6]	3.45	7.88	0.87	1.71	3.29	0.54
CVM [6]	3.53	7.89	0.83	-	-	-
Ours	**1.82**	**4.06**	**0.63**	**1.06**	**1.90**	**0.26**

Table 1: Quantitative results. Our model outperforms all map-free baselines by a large margin.

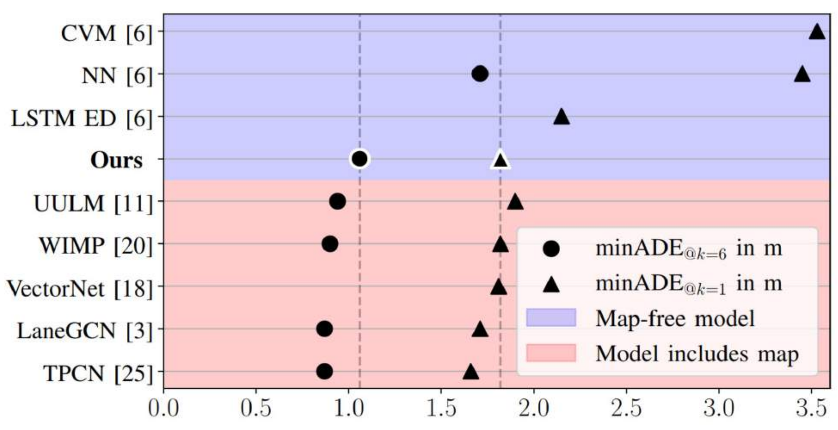

Figure 3: Comparison with models that use an HD map. text (© Mercedes-Benz AG)

Self-Attention as a Score for Social Interactions

- Limit the vehicles (social context) to target agent and L_s other agents
- Two selection strategies:
  1) Euclidean selection (blue): L_s vehicles that have the lowest Euclidean distance to the target vehicle
  2) Attention-based selection (orange): L_s vehicles that have the highest attention weights to the target vehicle during the forward pass of our model
- Training and evaluation of LaneGCN [3] on the subsets

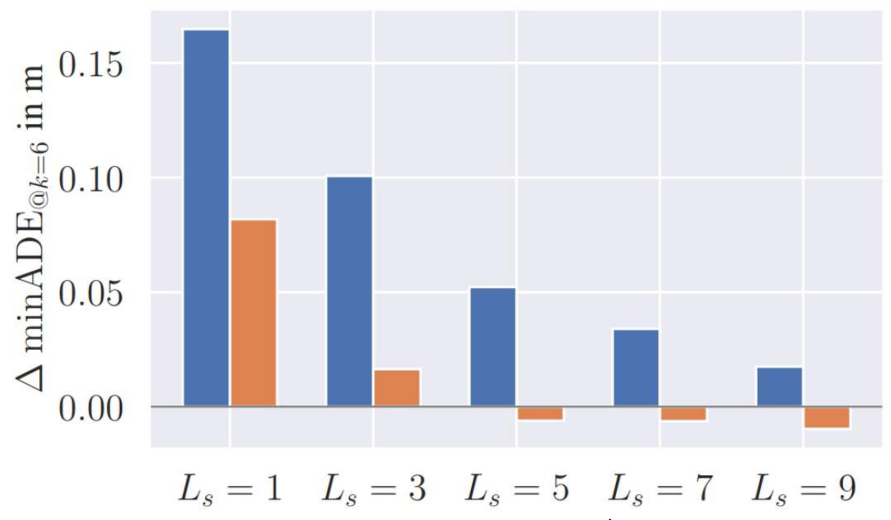

Figure 4: Interaction score evaluation (© Mercedes-Benz AG)

- Attention-based selection is able to extract the most relevant surrounding vehicles
- Attention weights can be interpreted as interaction scores

References:

[3] M. Liang, B. Yang, R. Hu, Y. Chen, R. Liao, S. Feng, and R. Urtasun, "Learning lane graph representations for motion forecasting", ECCV, 2020.
[6] M.-F. Chang, J. Lambert, P. Sangkloy, J. Singh, S. Bak, A. Hartnett, D. Wang, P. Carr, S. Lucey, D. Ramanan, and J. Hays, "Argoverse: 3d tracking and forecasting with rich maps", CVPR, 2019.
[11] J. Strohbeck, V. Belagiannis, J. Muller, M. Schreiber, M. Herrmann, D. Wolf, and M. Buchholz, "Multiple Trajectory Prediction with Deep Temporal and Spatial Convolutional Neural Networks", IROS, 2020.
[18] J. Gao et al., "VectorNet: Encoding HD Maps and Agent Dynamics From Vectorized Representation", CVPR, 2020.
[20] S. Khandelwal, W. Qi, J. Singh, A. Hartnett, and D. Ramanan, "Whatif motion prediction for autonomous driving", 2020.
[25] M. Ye, T. Cao, and Q. Chen, "Tpcn: Temporal point cloud networks for motion forecasting", CVPR, 2021.

Partners

External partners

For more information contact:

julian.sj.schmidt@mercedes-benz.com

KI Delta Learning is a project of the KI Familie. It was initiated and developed by the VDA Leitinitiative autonomous and connected driving and is funded by the Federal Ministry for Economic Affairs and Climate Action.

KI FAMILIE

www.ki-deltalearning.de @KI_Familie KI Familie

Supported by:
Federal Ministry for Economic Affairs and Climate Action
on the basis of a decision by the German Bundestag