

Improving Out-of-Distribution Generalization of Trajectory Prediction for Autonomous Driving via Polynomial Representations



Yue Yao^{1,2}, Shengchao Yan³, Daniel Goehring², Wolfram Burgard⁴, Joerg Reichardt¹

¹Continental AG, ²Freie Universität Berlin, ³University of Freiburg, ⁴University of Technology Nuremberg

For more information contact: yue.yao@continental.com

Motivation

Safe and comfortable driving requires to predict future actions of other traffic participants. Prediction algorithms should combine accuracy and speed with robustness against changes in the data distribution. We present a new prediction model that combines all of these traits.

Technical Problem

In a single motion dataset, test examples share similarities with the training samples, such as the sensor setup, map representation, post-processing, geographic, and scenario selection biases employed in dataset creation. Consequently, the test scores reported in each motion competition are examples of **In-Distribution (ID)** testing.

The differences in the data collection processes and sensor platforms between motion datasets of different origin present us with the opportunity to perform **Out-of-Distribution (OoD)** testing on truly independent data samples. However, this also comes with the challenges of working around inconsistencies in data formats and prediction tasks between datasets.

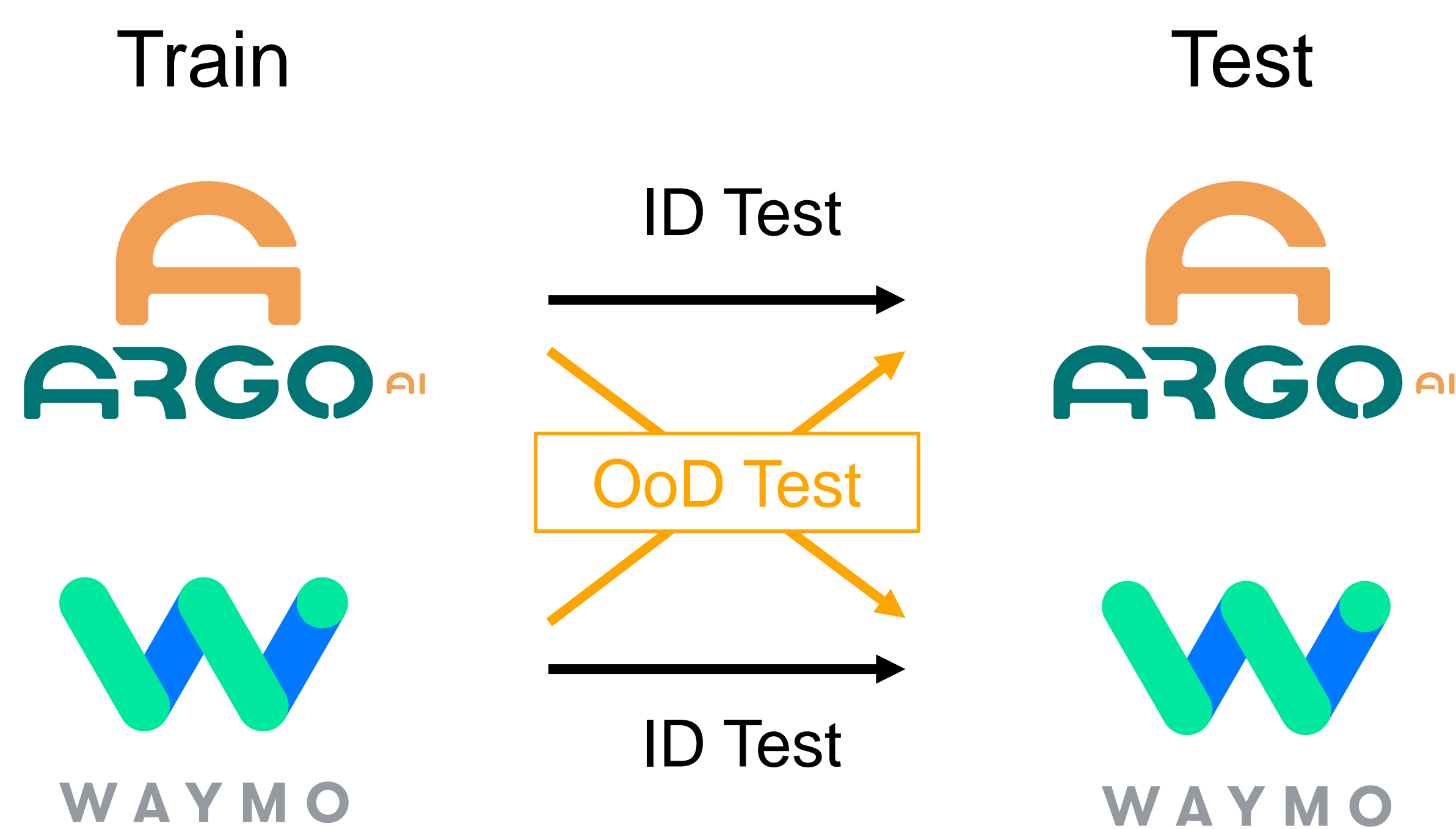


Figure 1: An illustration for In-Distribution and Out-of-Distribution tests between Argoverse 2 [1] and Waymo Motion [2] Datasets (© Continental AG)

Contributions:

- A dataset homogenization protocol that enables OoD testing of prediction algorithms across different large-scale motion datasets.
- Study of the OoD robustness of two SotA models and explore the effect of their augmentation strategies on ID and OoD test results.
- An efficient multi-modal predictor baseline with competitive ID performance and superior OoD robustness by representing trajectories and map features parametrically as polynomials (proposed and validated in [3, 4]).

References:

- [1] B. Wilson et al., Argoverse 2: Next generation datasets for self-driving perception and forecasting. NeurIPS, 2021.
 [3] Y. Yao et al., An Empirical Analysis of Object Trajectory Representation Models. ITSC, 2023.
 [5] Z. Zhou et al., Query-centric trajectory prediction. CVPR, 2023.

- [2] S. Ettinger et al., Large scale interactive motion forecasting for autonomous driving: The waymo open motion dataset, ICCV, 2021.
 [4] J. Reichardt, Trajectories as Markov-States for Long Term Traffic Scene Prediction. In 14th UniDAS FAS-Workshop, Berkheim, 2022.
 [6] J. Cheng et al., Forecast-mae: Self-supervised pretraining for motion forecasting with masked autoencoders. ICCV, 2023.

Results vs. SotA models

- Near-SotA In-Distribution performance with:
 - only 3.4% decrease in prediction accuracy
 - only 40.8% of the input data size
 - only 4.5% of the model size
 - only 3.9% of the model inference time
- Significantly improved robustness with reduced “performance drop” over SotA models in Out-of-Distribution test cases

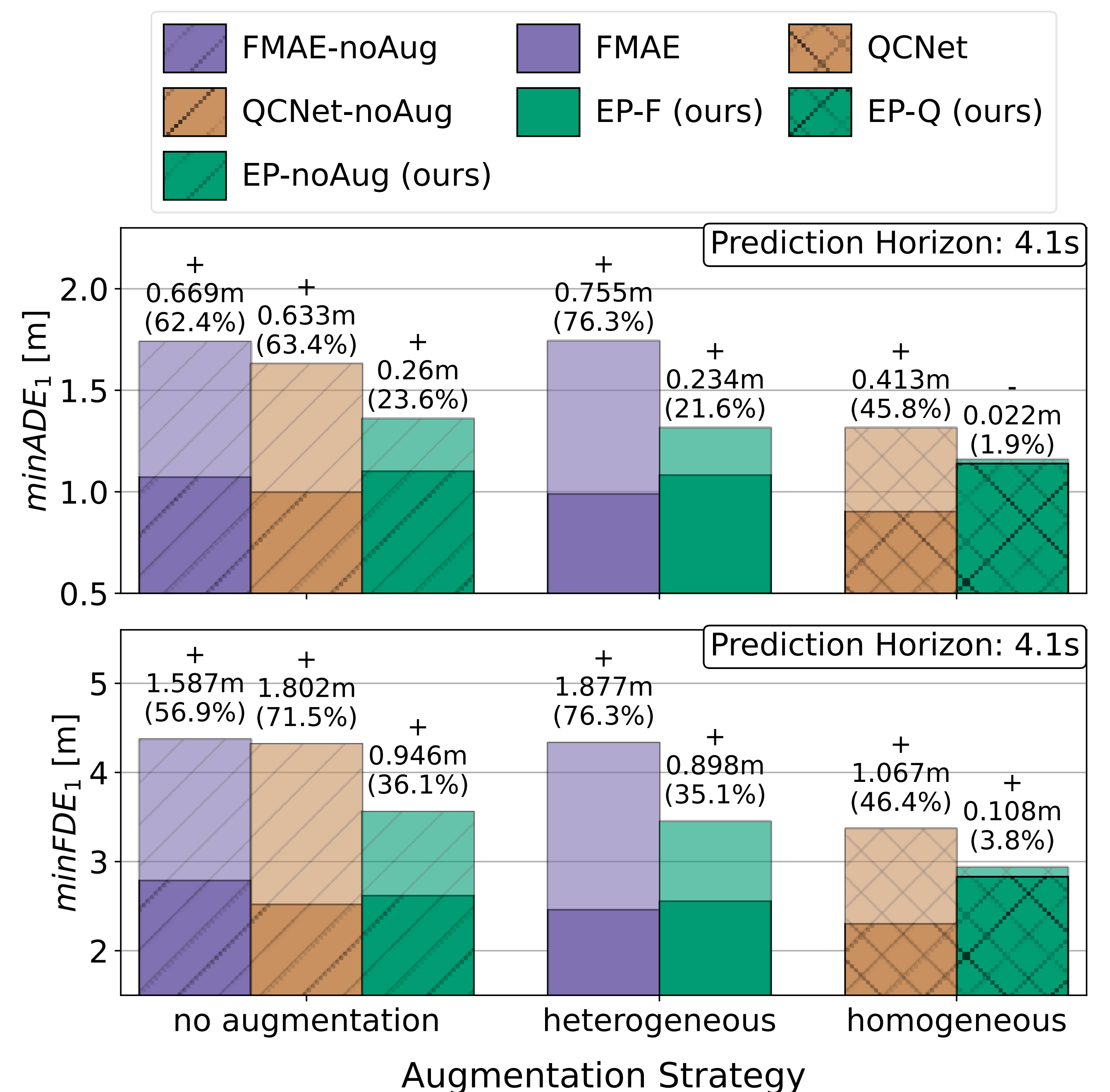


Figure 2: The OoD testing results of QCNet [5], Forecast-MAE (FMAE) [6], EP and their variants. We indicate the absolute and relative difference in displacement error between ID and OoD results. **Solid**: The ID results by training on the homogenized Argoverse2 training set and testing on the homogenized Argoverse2 validation set. **Transparent**: The increased displacement error in OoD testing by training on the homogenized Argoverse2 training set and testing on the homogenized Waymo validation set. (© Continental AG)

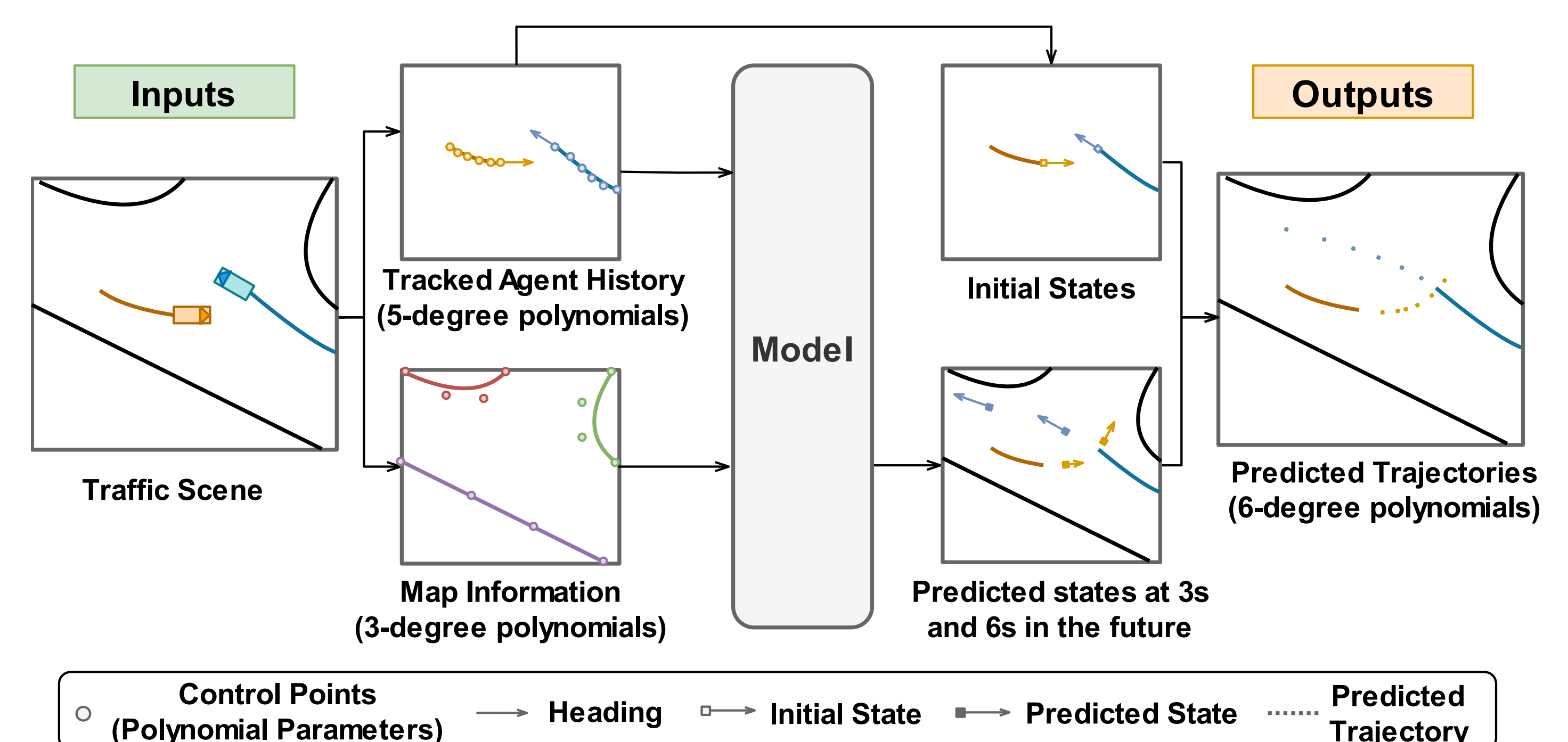


Figure 3: Our proposed model architecture. **Inputs**: Agent histories and road geometry are both represented via polynomials. **Outputs**: The current object kinematics and future kinematic states predicted by the model are fused into one continuous polynomial trajectory prediction. (© Continental AG)