

Uncertainty Quantification and Transfer Learning in Transformer based Model: A Case Study of Autonomous Driving

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Abstract

This thesis investigates uncertainty quantification and transfer learning for a transformer-based autonomous driving model. The task is formulated as supervised trajectory prediction, mapping multi-camera inputs to future trajectories. Directly transferring the performance of the model from the source domain (urban passenger cars) to the target domain (highway heavy trucks) is difficult due to significant differences in camera setups, vehicle dynamics, environments, etc.

A two-stage fine-tuning procedure is applied to address these domain gaps. This two staged procedure revealed that fine-tuning the latent representation while freezing downstream components substantially improves target-domain object detection by realigning pre-trained knowledge. End-to-end fine-tuning further improves trajectory accuracy by adapting predictions to target-domain motion patterns while maintaining plausible prediction behaviour.

We also study uncertainty quantification using Conformalized Quantile Regression. Raw Quantile Regression lacks reliable calibration guarantees, and therefore, Conformal calibration applied on top of Quantile regression achieves the desired empirical coverage across all prediction horizons and axes. The resulting conformalized intervals behave intuitively, widening over time and in heteroscedastic scenes.

The results show that Transfer learning effectively adapts the pre-trained model to the heavy-truck domain, proving superior to learning from scratch despite some remaining gaps. Furthermore, conformal calibration provides vital reliability information, establishing a strong foundation for uncertainty-aware trajectory prediction.

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