

Neural Network-Based Trajectory Prediction with Criticality Metrics: Feature Analysis and Model Optimization

Master's Thesis of Mykyta Yevtushenko

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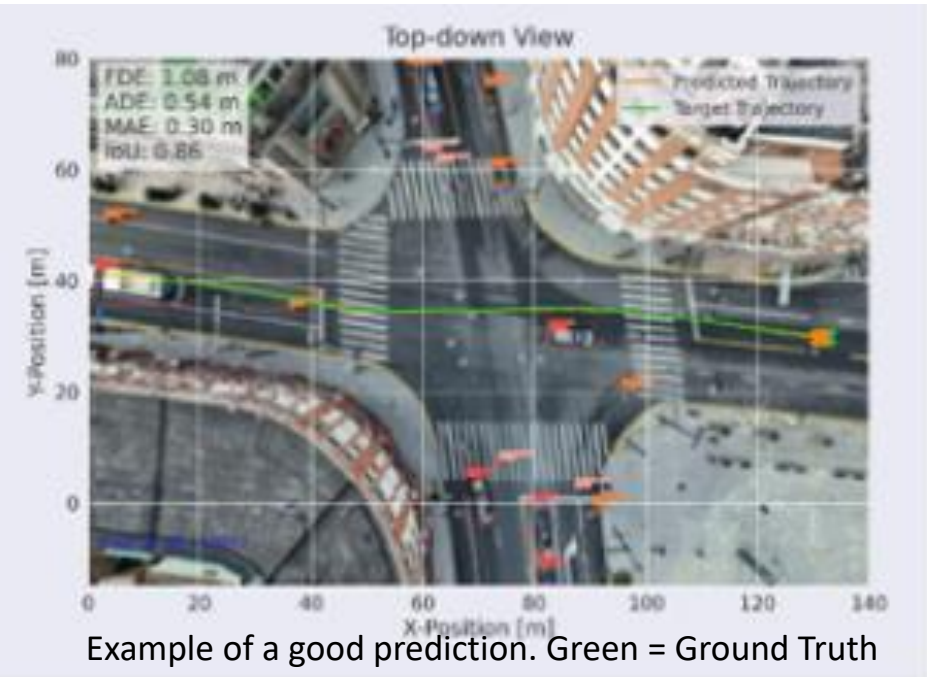
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Driving Simulator at BMW AG

Approach

A deep-learning trajectory prediction approach based on an attention-based encoder and LSTM decoder processes historical motion data to generate multi-step future trajectory predictions, yet current models lack consideration of interactions with other traffic participants, reducing accuracy. Using data from a large urban intersection in Sichuan, originally containing only x/y coordinates, frame IDs, and track IDs for 960 participants, including 400 motorbikes, this work expands the feature space with criticality metrics (CMs) commonly applied in autonomous driving. These metrics describe how dangerous a trajectory is by accounting for surrounding agents and were selected based on scenario coverage, sensitivity, and real-time suitability. The integrated CMs include Headway, Time-Headway, Time-To-Collision, Time-To-Zebra, Delta-V, Collision Probability, and IUTQ. Additional interaction-focused features—such as occupied spaces, Top-K participants (distance- and TTC-based), and relative motion descriptors from the ego-vehicle perspective—enable richer modeling of potential interactions and improved prediction fidelity.



Example of a good prediction. Green = Ground Truth
Orange = Prediction

Introduction

Simulations play a critical role in the vehicle development cycle, yet a persistent simulation–reality gap limits their effectiveness. Realistic modeling of road agents—particularly motorbikes and scooters—is essential, as road-user interactions in large urban intersections are highly complex. Existing VRU-specific research is limited, especially for motorbikes, with key challenges including the lack of datasets and the need for domain-specific models. Prior work, such as the deep-learning approach introduced by Causevic et al., uses relatively simple datasets containing many VRUs, highlighting the need for more refined methods. This work analyzes an existing dataset to identify and integrate new behavioral features into a neural-network-based prediction framework, aiming to improve trajectory prediction accuracy across varying prediction horizons. Addressing the challenge of accurately forecasting scooter trajectories enhances the realism of traffic simulations, enabling more reliable evaluation of driver interactions and advanced assistance systems.

Experiment	Comment
01	Basic NN + Basic features by [2]
02	Basic NN + Full feature set (basic and newly computed)
03	Basic NN + Full feature set + manually reduced CMs
04	Basic NN + PCA-reduced full feature set
05	Basic NN + Full feature set + PCA reduced CMs
06	Basic NN + feature selection via BO - basic configuration from step 0
07	Basic NN + feature selection via BO - basic configuration from step 150
08	Basic NN + feature selection via BO - 20 random initial samples
09	NAS and feature selection at the same time
10	just NAS and basic features
11	feature selection, after performing NAS in 10

Experiment overview

10 | 3.79854 | 6.78283 | 0.45403
Performance for best experiment (ADE | FDE | IoU)

Results

Experimental results indicate that introducing additional features did not enhance prediction accuracy, as the added inputs introduced noise, leaving the basic feature set as the most robust. A neural architecture search (NAS) using this simpler input configuration achieved the best performance, though notable inaccurate predictions still occurred. Adjusting input–output sequence lengths showed only minor influence, confirming that data quality and model architecture matter more than sequence tuning. Several factors limit performance: static criticality metrics, tracking errors, missing or imbalanced data, lack of lane-level context, simplified motorcycle dynamics, and insufficient behavioral diversity, all hindering generalization. Overall, the model lacks the spatio-temporal reasoning required for reliable real-world deployment, and current prediction errors remain too large for practical use.