2.9 Learning-Aided Warmstart of Model Predictive Control in Uncertain Fast-Changing Traffic

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Trajectory Prediction and Motion Planning

Motivation

Purely learning-based motion planning and control approaches lack reliability which limits their suitability for safety-critical applications. While Model Predictive Control (MPC) offers safety and feasibility guarantees, it faces problems of convergence in fast changing, uncertain environments and dense traffic. Here, on the other hand, learning-based methods excel due to their ability to handle the complex and uncertain nature of other traffic participants behavior.

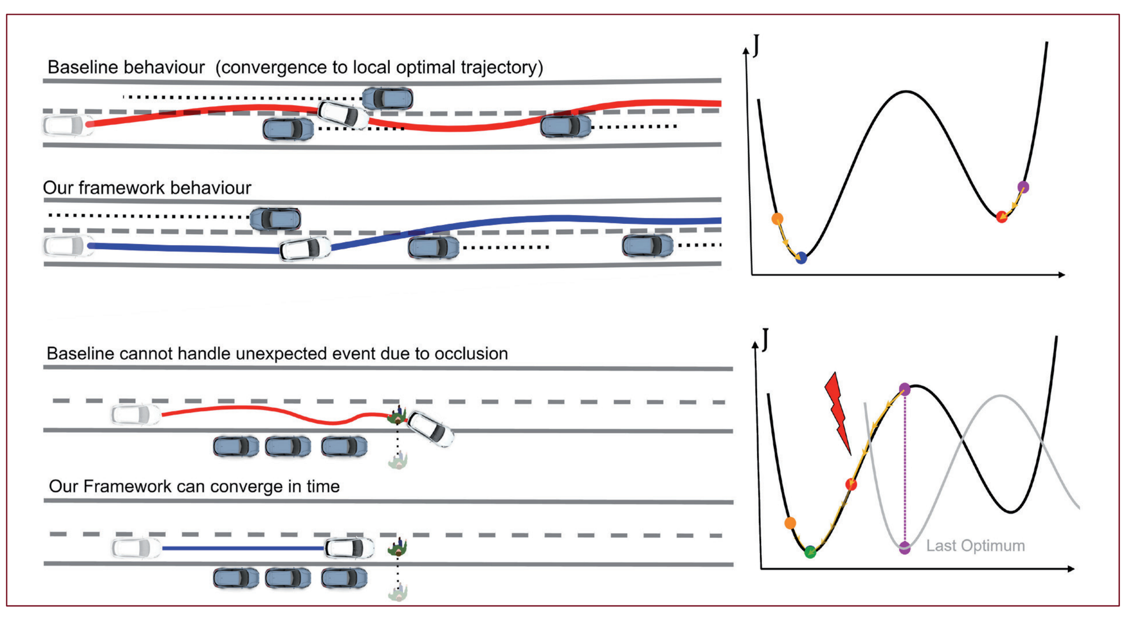


Figure 1: Example of MPC's two main limitations and our improvements

Technical Solution

Due to their complementary attributes, we propose to combine MPC with a learning-based approach. Our framework leverages a neural network to provide learning-aided warmstarts of MPC algorithms. The learning-based approach outputs a trajectory for the ego vehicle which is used as an initial guess and then further optimized (e.g., filtering out collisions, making the trajectory dynamically feasible, etc.) by the MPC. This initialization of the optimizer improves the convergence quality of the MPC.

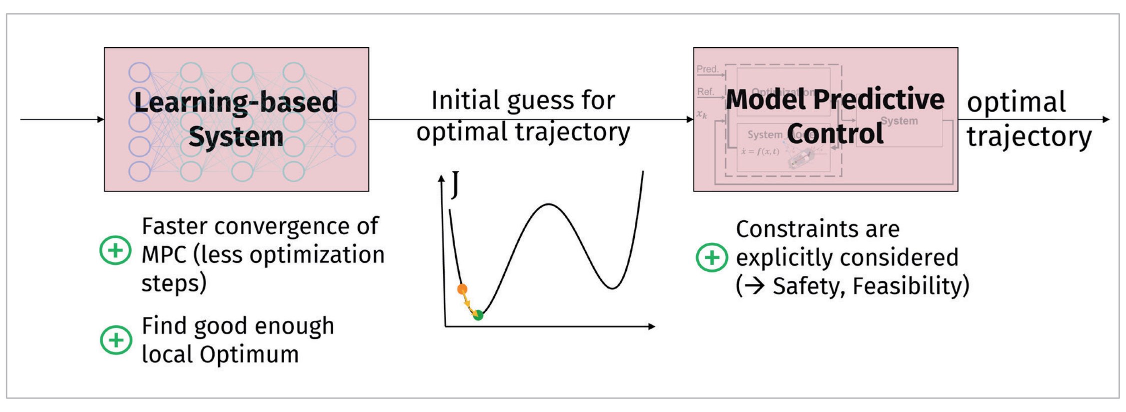
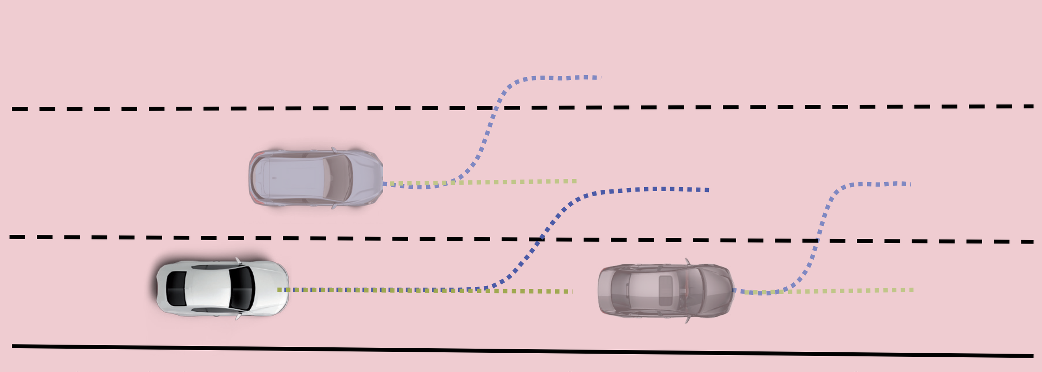


Figure 2: The framework optimally combines MPC and learning-based approaches, synergizing their strengths to enhance performance and safety

Results

Our approach significantly improves convergence quality and hence performance of the autonomous vehicle in a wide range of scenarios.

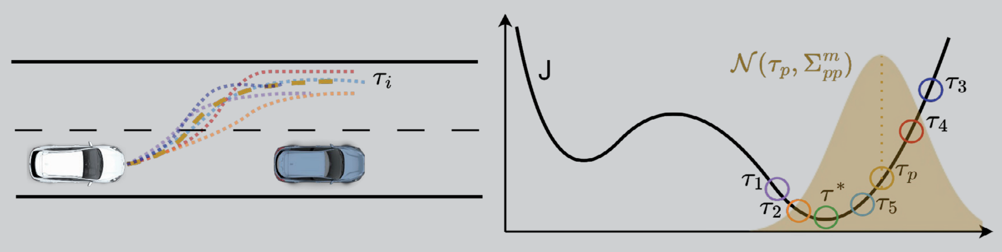
Learning-Based Predictor



Capitalizing on the necessity for a predictor, we reutilize it for the ego trajectory.
SotA predictors are multimodal, i.e., with diverse predictions for road user behaviors.
Our approach leverages the multi-modal output to identify multiple local optima.

Predictions of ego | Predictions of road users

Trajectory Mode Refinement



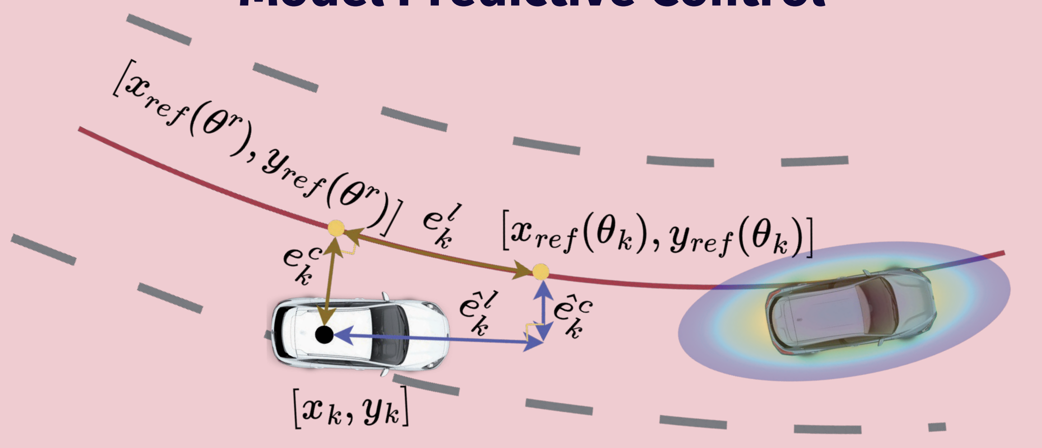
Bayesian linear regression extracts a continuously differentiable trajectory from the discrete predictor output (waypoints). Subsequently, we employ parallelized sampling-based optimization to obtain a better guess to the respective local optima.

Trajectory proposals

Select trajectory mode with minimum objective function value as warmstart

Initial Guess

Model Predictive Control



The MPC generates optimal trajectories accounting for collision constraints, dynamic feasibility, actuator constraints, and comfort criteria.

References

[1] Bouzidi et al.: Learning-Aided Warmstart of Model Predictive Control in Uncertain Fast-Changing Traffic, IEEE International Conference on Robotics and Automation (ICRA), 2024

	Merging Execution			Convergence Quality			
	Success	Aborted	Collision	Success	Time Constraint Violation	Convergence to Infeasibility	Average Cost
Baseline MPC	73%	11%	16%	69.3%	13.6%	17.1%	4995
Ours	**88%**	**4%**	**8%**	**82.7%**	**7.0%**	**10.3%**	**3737**

Table 1: Comparison of baseline and the learning-aided framework using Monte Carlo Analysis of merging maneuvers

Partners

External partners

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