Interactive Motion Planning with Learning-based Optimal Control

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VOLVO

Stochastic Optimal Control over Scenario Trees

- Other vehicles in the environment are modelled as Markov systems, with discrete and finite action set Ξ.

$$\xi \sim P_\xi(\bar{\mathbf{x}}) = (\mathbb{P}\{\xi = \mathrm{m} \mid \bar{\mathbf{x}}\})_{m\in\Xi}$$
$$\mathbf{u} = \pi(\bar{\mathbf{x}}, \xi)$$

- Realizations of the uncertain environment are enumerated to create a scenario tree.

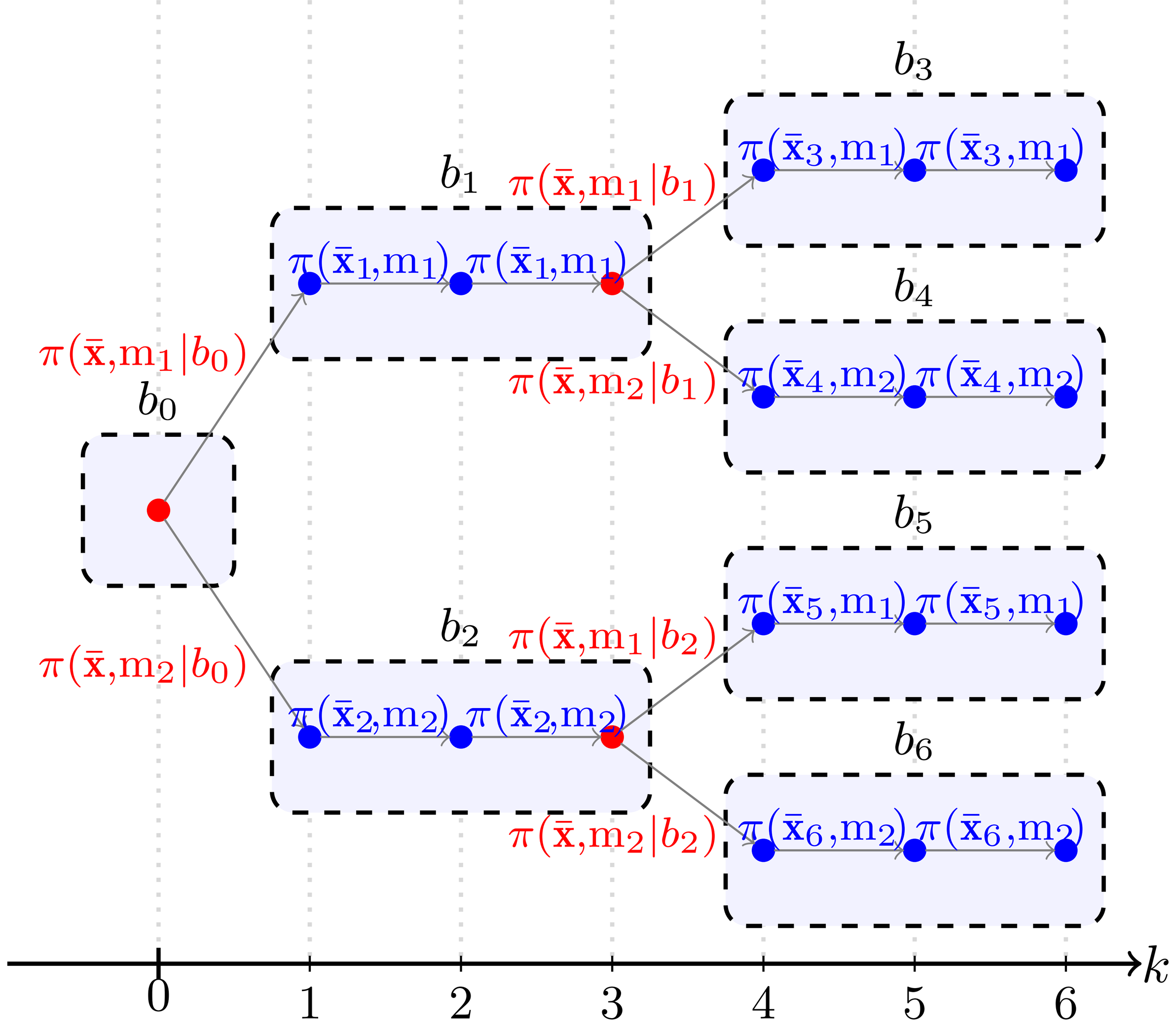


Fig. Approximation of a scenario tree considering one other vehicle with two actions.

- Uncertainty estimates are expressed by propagating transition probabilities through the scenario tree.

$$p_{\text{child}}(\bar{\mathbf{x}}) = p_{\text{Parent}} \cdot P_\xi(\bar{\mathbf{x}}_{\text{parent}} | \xi = \mathrm{m})$$

- Collision avoidance constraints are formulated as chance constraints, based on the transition probabilities and accepted violation rate ε.

$$\mathbb{P}[\mathrm{dist}(\mathbf{x}_{\text{ego}}, \mathbf{x}_{\text{adj}}) \leq d_{\text{safe}}] \leq \varepsilon \iff$$
$$\mathbb{E}\left[\mathbf{I}_{(0,\infty)}(d_{\text{safe}} - \mathrm{dist}(\mathbf{x}_{\text{ego}}, \mathbf{x}_{\text{adj}}))\right] \leq \varepsilon \iff$$
$$\sum_{\substack{\text{Relevant}\\\text{nodes}}} \hat{p}(\mathbf{x}_{\text{ego}}, \mathbf{x}_{\text{adj}}) \cdot \mathbf{I}_{(0,\infty)}(d_{\text{safe}} - \mathrm{dist}(\mathbf{x}_{\text{ego}}, \mathbf{x}_{\text{adj}})) \leq \varepsilon$$

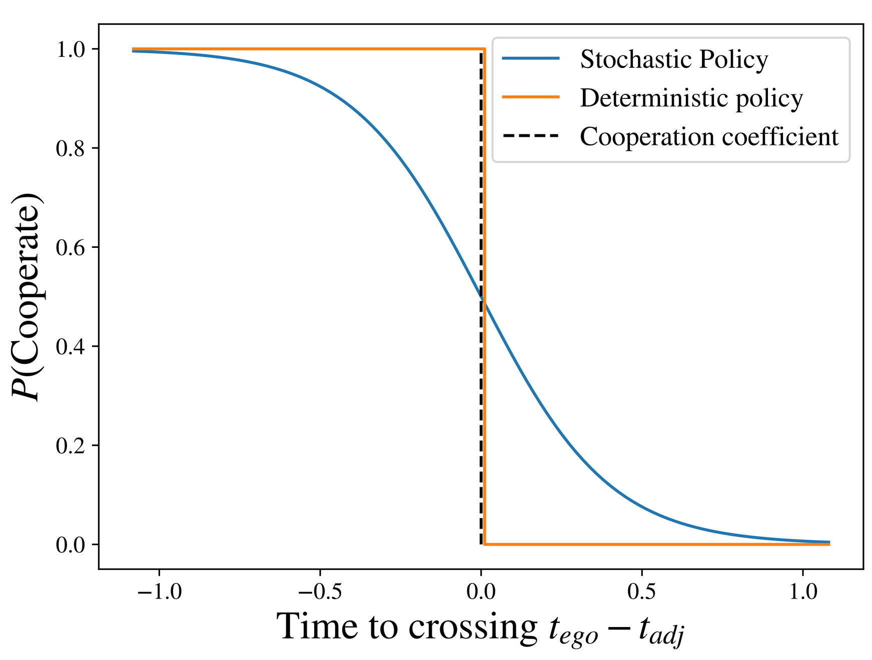
- Conditional distribution of state transitions is estimated with computationally efficient learning-based techniques.

Logistic Regression

$$\hat{p}_i(\bar{\mathbf{x}}) = \frac{\exp(\theta_i^\top \varphi(\bar{\mathbf{x}}))}{\sum_{i=1}^{N_\xi} \exp(\theta_i^\top \varphi(\bar{\mathbf{x}}))}$$

θ - Learnable Weights
$\varphi(\bar{\mathbf{x}})$ - Selected Feature Vector

Ground-Truth Distribution Examples



- Expected performance of the ego-vehicle is optimized.

$$\ell(\mathbf{x}_{\text{ego}}, \mathbf{u}_{\text{ego}}) = ||\mathbf{x}_{\text{ego}} - \mathbf{x}_{\text{ref}}||^2_{\mathbf{Q}} + ||\mathbf{u}_{\text{ego}}||^2_{\mathbf{R}} + ||\Delta\mathbf{u}_{\text{ego}}||^2_{\mathbf{R}_\Delta}$$

$$\min_{\mathbf{x}_{\text{ego}}, \mathbf{u}_{\text{ego}}} \mathbb{E}_\xi \left[\ell_N(\mathbf{x}_{\text{ego}}(N)) + \sum_{k=0}^{N-1} \ell(\mathbf{x}_{\text{ego}}(k), \mathbf{u}_{\text{ego}}(k))\right]$$

Applications in Autonomous Driving

- Lane Merging in Dense traffic for a Heavy Vehicle combination.

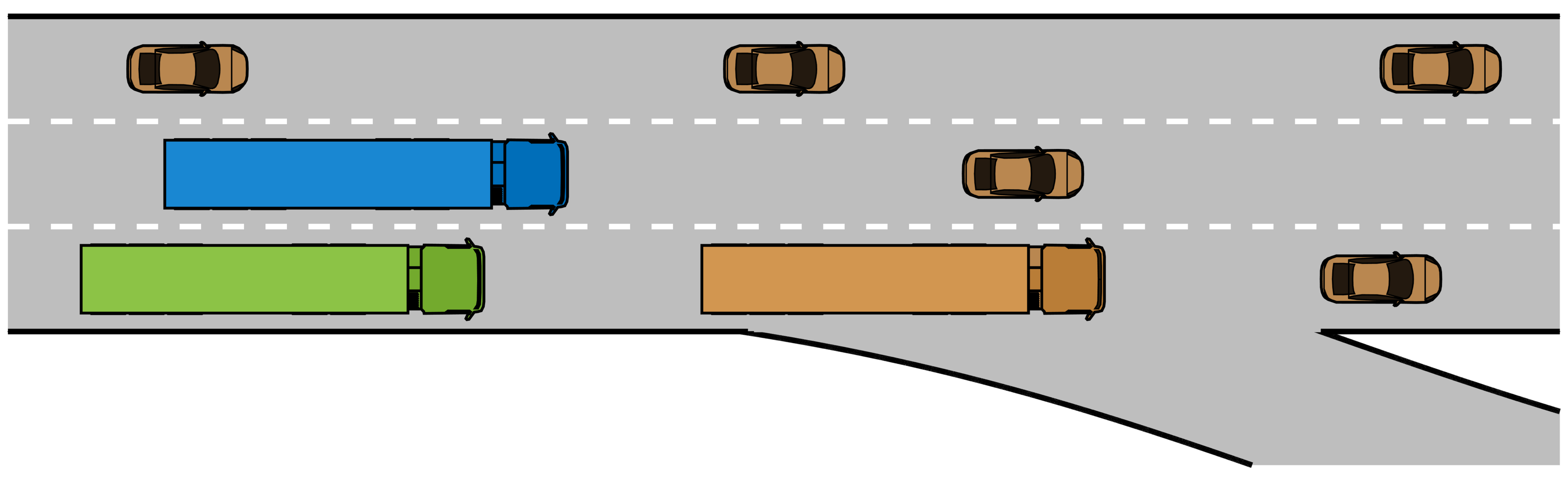


Fig. Traffic scenario with interactive maneuvers between Heavy vehicles.

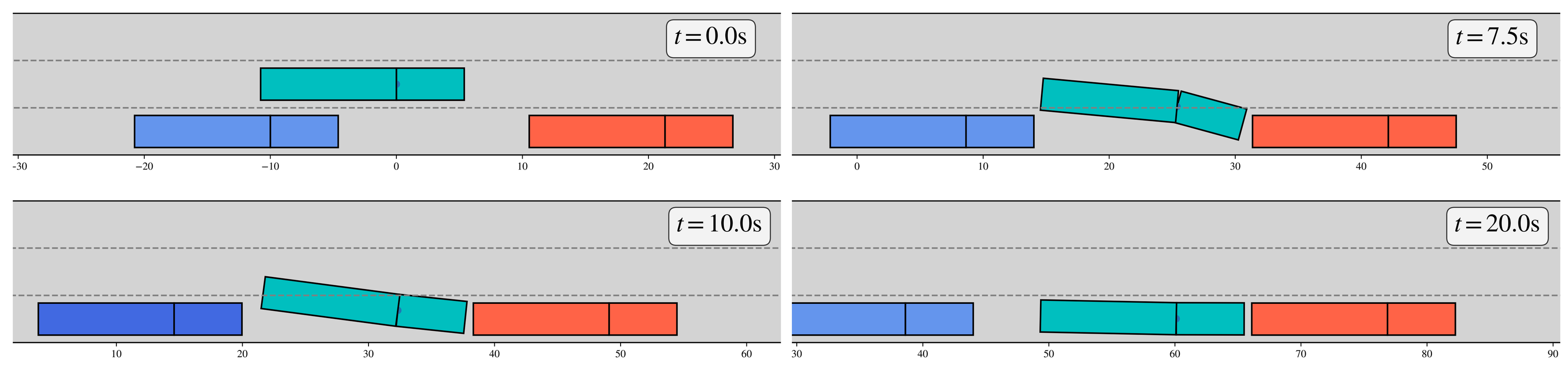


Fig. Lane merging maneuver for heavy vehicle.

- Negotiating with Human Drivers at Intersections.

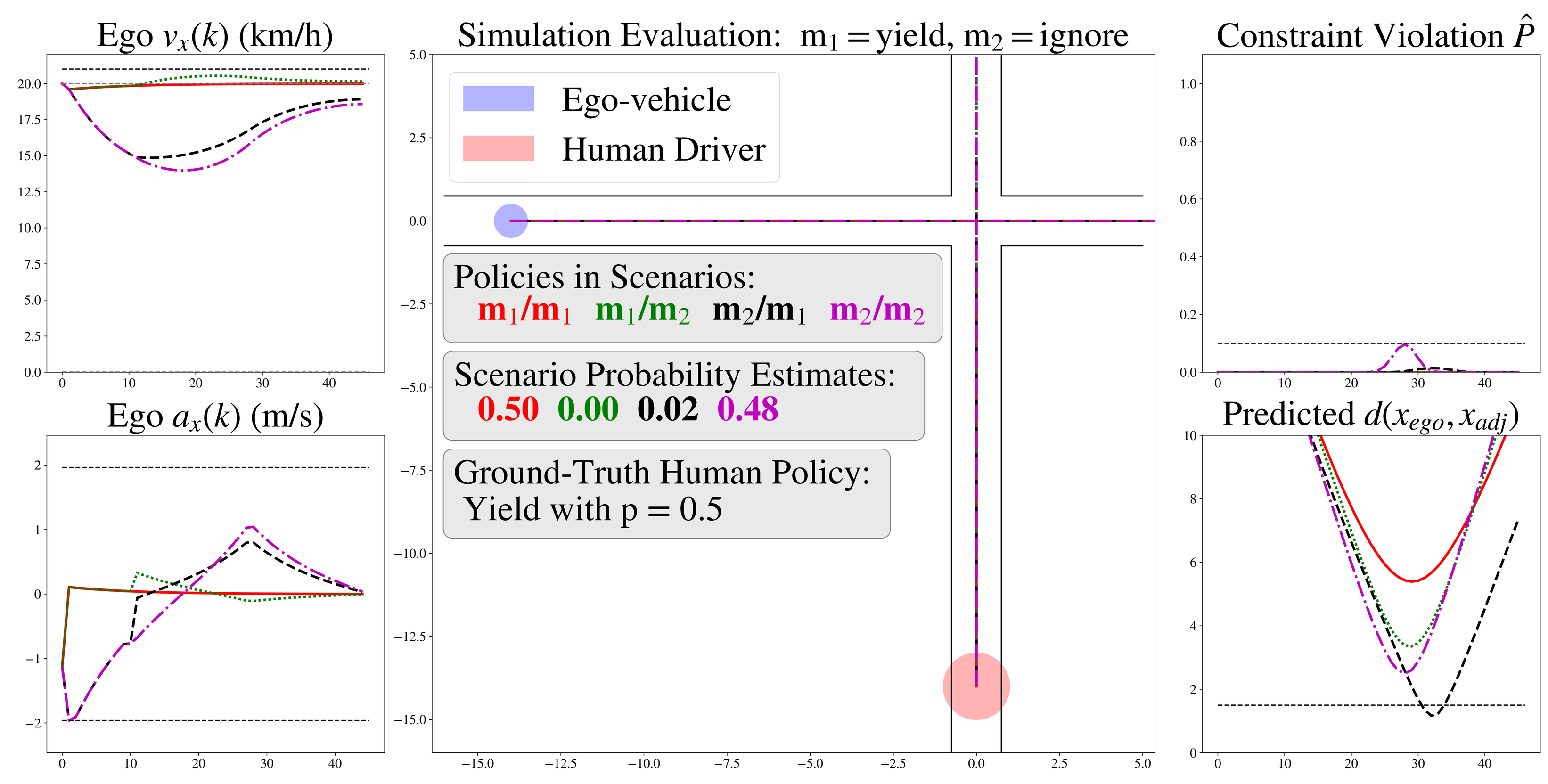


Fig. Intersection scenario with Corresponding Optimal Control Solution.

Nice Properties

- Avoids excessively conservative behavior.
- Human-like reasoning can be observed.
- Risk vs Performance can be tune via ε.

Interesting Challenges

- Feasibility Guarantees with ML Methods.
- Tight, and Efficient Chance Constraints
- Guarantees with Tree Approximations.

Publications

[1] Interaction-Aware Trajectory Prediction and Planning in Dense Highway Traffic using Distributed Model Predictive Control
Erik Börve, Nikolce Murgoski and Leo Laine,
Conference on Decision and Control, 13-15 Dec., 2023, Singapore