2.3 An Empirical Bayes Analysis of Object Trajectory Representation Models [1]

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Trajectory Prediction and Motion Planning

Motivation

- Past and future motion of traffic participants are restricted by physical constraints.
- Trajectory tracking and prediction methods must respect and should utilizes these constraints for regularization.
- We propose an interpretable, physically informed, and efficient parametric trajectory representations as a fundamental building block of tracking and prediction algorithms.

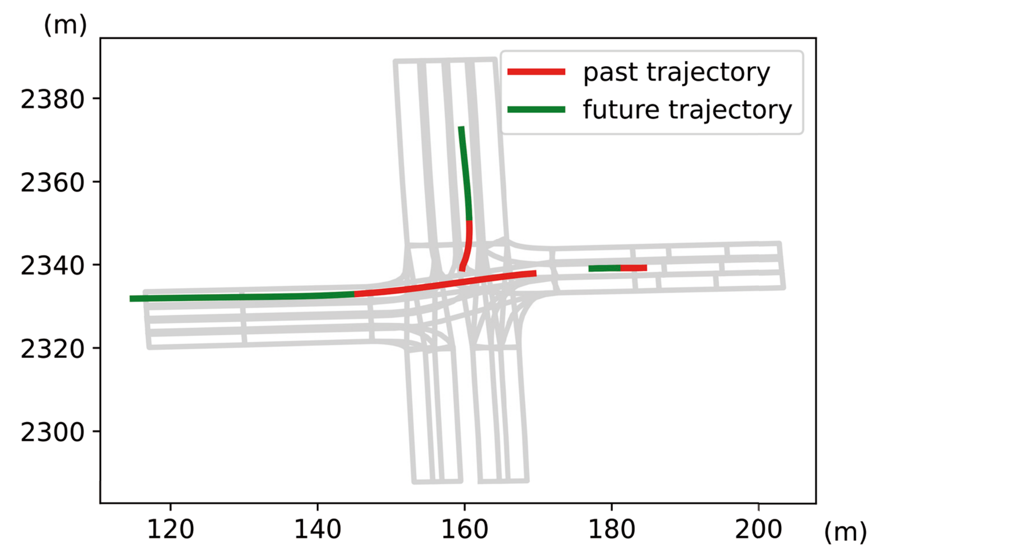

Figure 1: Example trajectories in Argoverse Motion Forecasting 1.1 [2]

Technical Problem

- Characterize the trade-off between model complexity and representation error.
- Estimate prior distributions over model parameters and observation noise from empirical data.

Technical Solution

A trajectory $\boldsymbol{c}(\tau) \in \mathbb{R}^{md}$ with m points is represented as a linear combination of $n+1$ polynomial basis functions $\boldsymbol{\Phi}(\tau) \in \mathbb{R}^{(n+1)d \times md}$ and model parameters $\boldsymbol{w} \in \mathbb{R}^{(n+1)d}$:

$$\boldsymbol{c}(\tau) = \boldsymbol{\Phi}^T(\tau)\,\boldsymbol{w} \qquad (1)$$

We formulate trajectories in datasets with Type-II likelihood based on parameters $\boldsymbol{\theta}$ for constructing observation covariance $\boldsymbol{\Sigma}_o(\boldsymbol{\theta})$ and model parameter covariance $\boldsymbol{\Sigma}_w$:

$$p(\mathbf{C}|\boldsymbol{\Sigma}_o(\boldsymbol{\theta}), \boldsymbol{\Sigma}_w) = \prod_{i=1}^{N} \int \mathcal{N}\left(\boldsymbol{c}_i^{ob} \middle| {\boldsymbol{\Phi}_i}^T \boldsymbol{w}, \boldsymbol{\Sigma}_{o,i}(\boldsymbol{\theta})\right) \mathcal{N}(\boldsymbol{w}|\mathbf{0}, \boldsymbol{\Sigma}_w)\,\mathrm{d}\boldsymbol{w}$$

$$= \prod_{i=1}^{N} \mathcal{N}\left(\boldsymbol{c}_i^{ob} \middle| \mathbf{0}, \boldsymbol{\Sigma}_{o,i}(\boldsymbol{\theta}) + {\boldsymbol{\Phi}_i}^T \boldsymbol{\Sigma}_w \boldsymbol{\Phi}_i\right) \qquad (2)$$

Where C denotes all N trajectories in the dataset and $\boldsymbol{c}_i^{ob}$ denotes the measurement of i^{th} trajectory. We maximize the log of (2) with respect to $\boldsymbol{\Sigma}_w$ and $\boldsymbol{\theta}$ for object trajectories of multiple types separately using gradient descent. These optima represent the prior parameters estimated from the dataset:

$$\hat{\boldsymbol{\theta}}, \hat{\boldsymbol{\Sigma}}_w = \mathrm{argmax}_{\boldsymbol{\theta}, \boldsymbol{\Sigma}_w}\, p(\mathbf{C}|\boldsymbol{\Sigma}_o(\boldsymbol{\theta}), \boldsymbol{\Sigma}_w) \qquad (3)$$

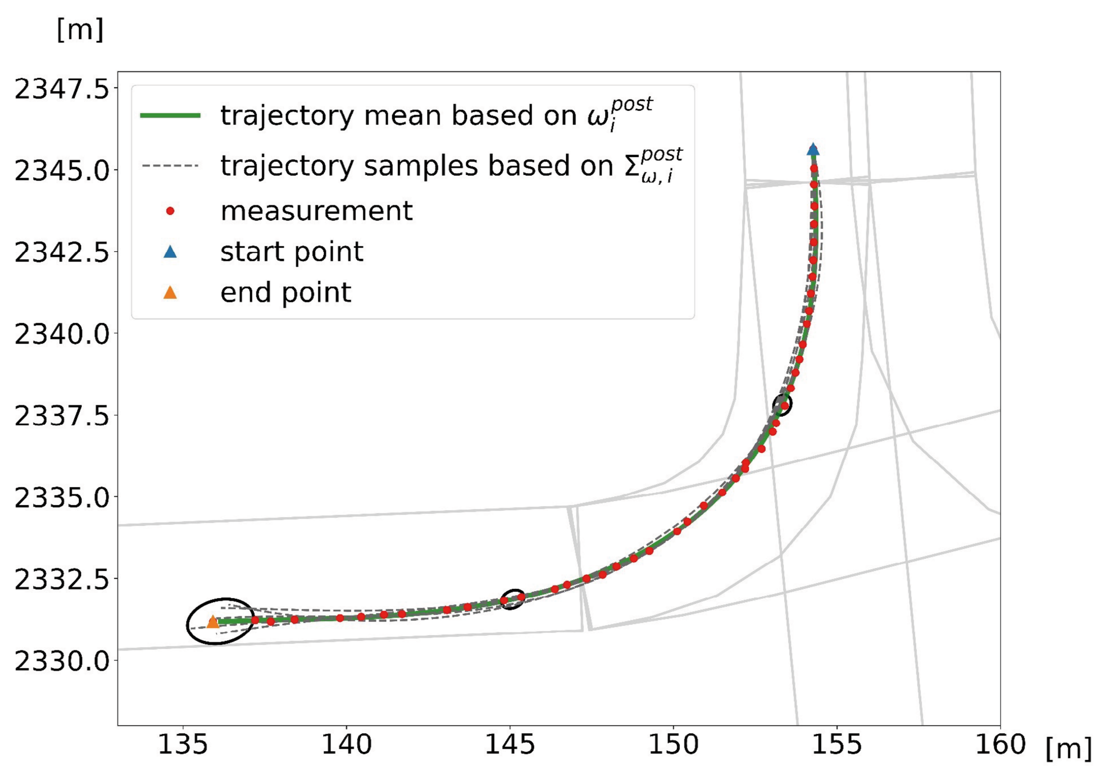

Figure 2: A typical scene from a trajectory prediction dataset, here Argoverse Motion Forecasting v1.1 [2]. The object trajectory fitted with a polynomial trajectory representation estimated via eq. (4). The resulting posterior covariances for agent positions are also shown, enlarged by a factor of 8 for better visibility. (© Continental AG)

Using this prior, the posterior estimate of model parameters for a single trajectory $\boldsymbol{c}_i$ is given in closed form:

$$\begin{aligned} \boldsymbol{\Sigma}_{w,i}^{post} &= (\boldsymbol{\Sigma}_w^{-1} + \boldsymbol{\Phi}_i \boldsymbol{\Sigma}_{o,i}^{-1} {\boldsymbol{\Phi}_i}^T)^{-1} \\ \boldsymbol{w}_i^{post} &= \boldsymbol{\Sigma}_{w,i}^{post} \boldsymbol{\Phi}_i \boldsymbol{\Sigma}_{o,i}^{-1} \boldsymbol{c}_i^{ob} \end{aligned} \qquad (4)$$

Results

- Real world trajectories over relevant time scales can be represented with high fidelity by simple linear models.
- The linear model enables efficient Kalman filtering of parameters [3].
- Trajectory prediction can then be formulated as a filtering problem [3].

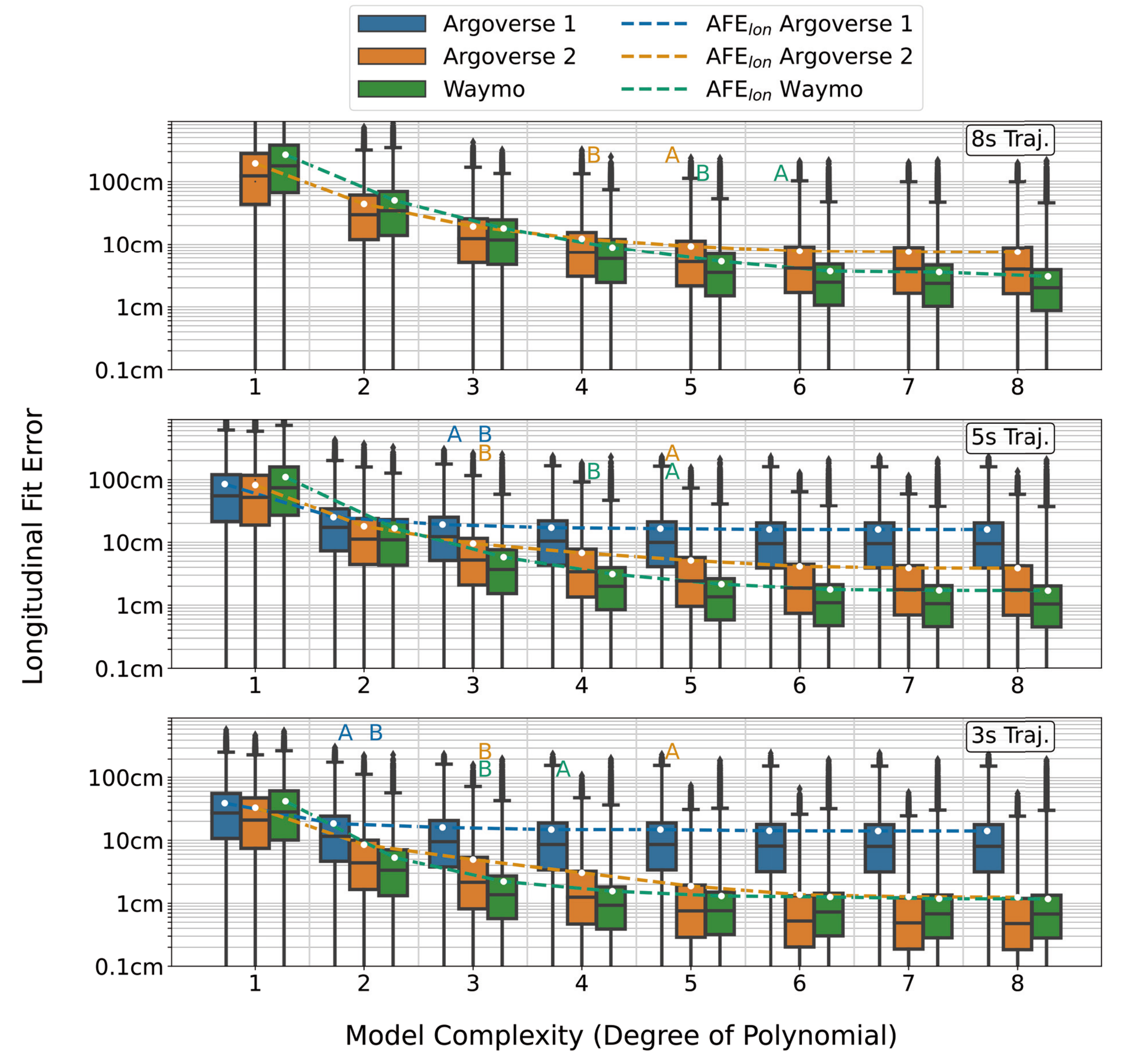

Figure 3: The longitudinal fit error of models for vehicle trajectories with T ∈[3s, 5s, 8s]."A, B" denote the model complexity $n = \hat{n}$ that maximizes AIC and BIC, respectively. The upper whisker denotes the 99.9% percentile. (© Continental AG)

References

[1] Y. Yao et al. An Empirical Analysis of Object Trajectory Representation Models. In proc. of ITSC, 2023, arXiv:2211.01696
[2] M.-F. Chang et al. Argoverse: 3D Tracking and Forecasting with Rich Maps. In CVPR, 2019
[3] J. Reichardt. Trajectories as Markov-States for Long Term Traffic Scene Prediction. In 14th UniDAS FAS-Workshop, Berkheim, 2022
[4] B. Wilson et al., "Argoverse 2: Next generation datasets for self-driving perception and forecasting". In NeurIPS, 2021.
[5] S. Ettinger et al., Large scale interactive motion forecasting for autonomous driving: The Waymo Open Motion Dataset. In CVPR, 2021

Partners

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