Online Sparse Gaussian Process Regression for Trajectory Modeling

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Overview

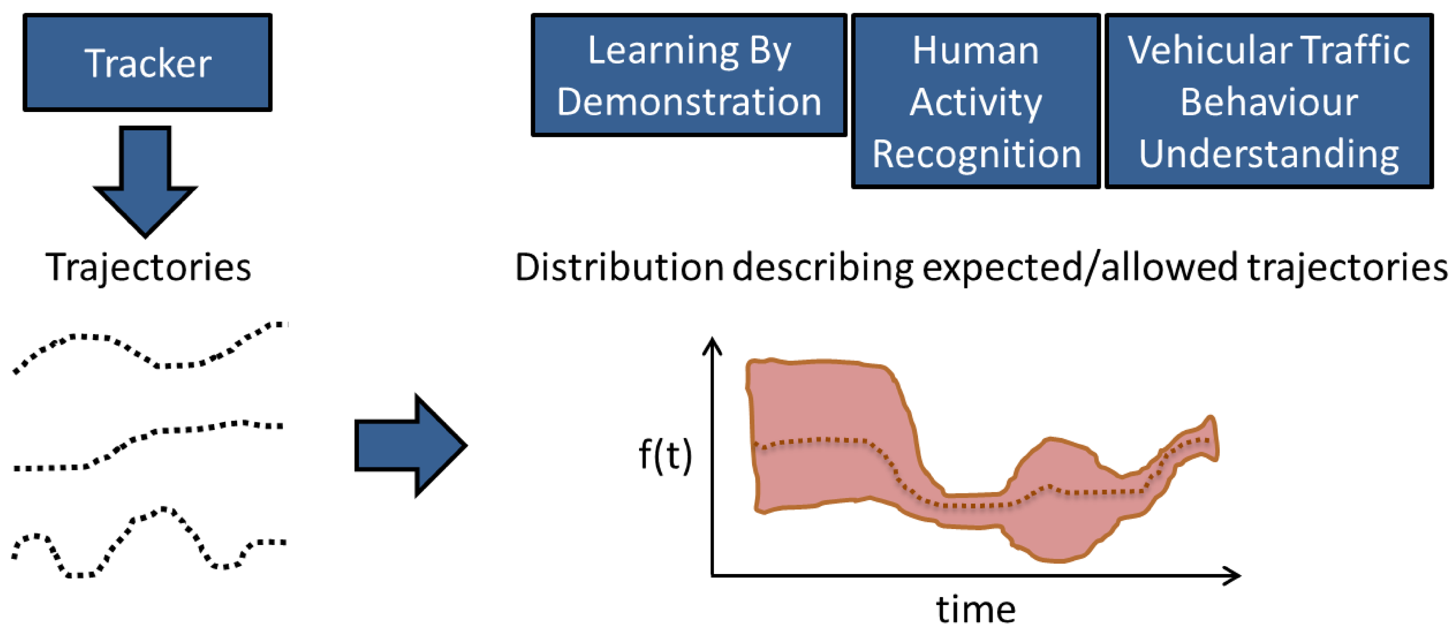
We consider the *problem of modeling a set of smooth trajectories*, each of which is observed as a set of noisy samples. This is relevant for many application areas such as learning by demonstration[3] and activity/behavior recognition[1][2]. We additionally consider how to do this *in an online setting* for applications that need to continue to learn in the field.

We propose fusion methods for mixture of Gaussian processes (MoGP) which provide good models for sets of trajectories both serial and parallel in the input space [4]. The MoGP model is further approximated with a single GP by solving a sparse inverse GP regression problem. *Batch and online algorithms* are presented for learning GP models with good complexity.

Our approach uses all available data (an improvement over [1]). The model size *does not grow with more data*. We present flexible split and merge techniques for model management and a *decreasing learning time* over time.

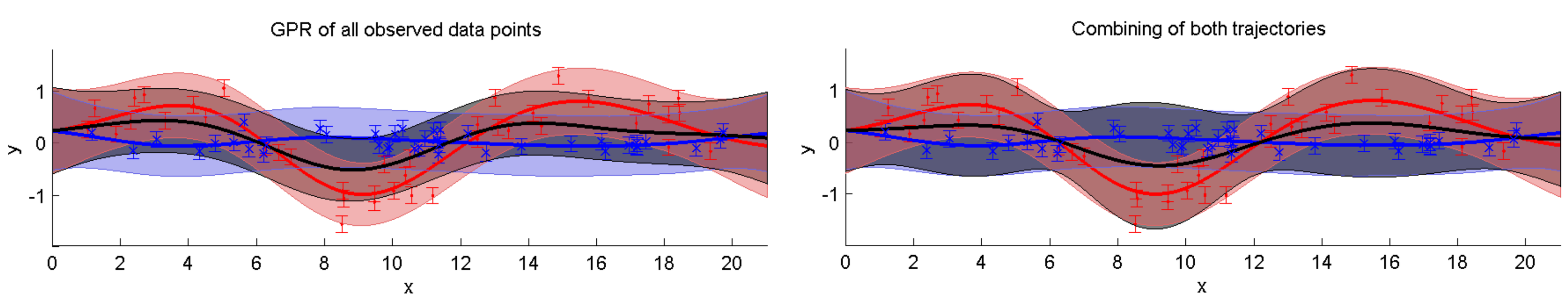
The Problem

Given a set of observed sparsely observed trajectories, how to model them in a way that capture the variance of expected or allowed trajectories (generalizing over the set). How to incorporate additional trajectories online?



Modeling Sets of Trajectories

Given two trajectories (red and blue) observed through noisy samples we seek a distribution over functions that generalize over them and capture expected future trajectories. Individual trajectories are modeled using Gaussian processes, a Bayesian non-parametric distribution over functions, which provide a mean-function and a variance-function through continuous time.

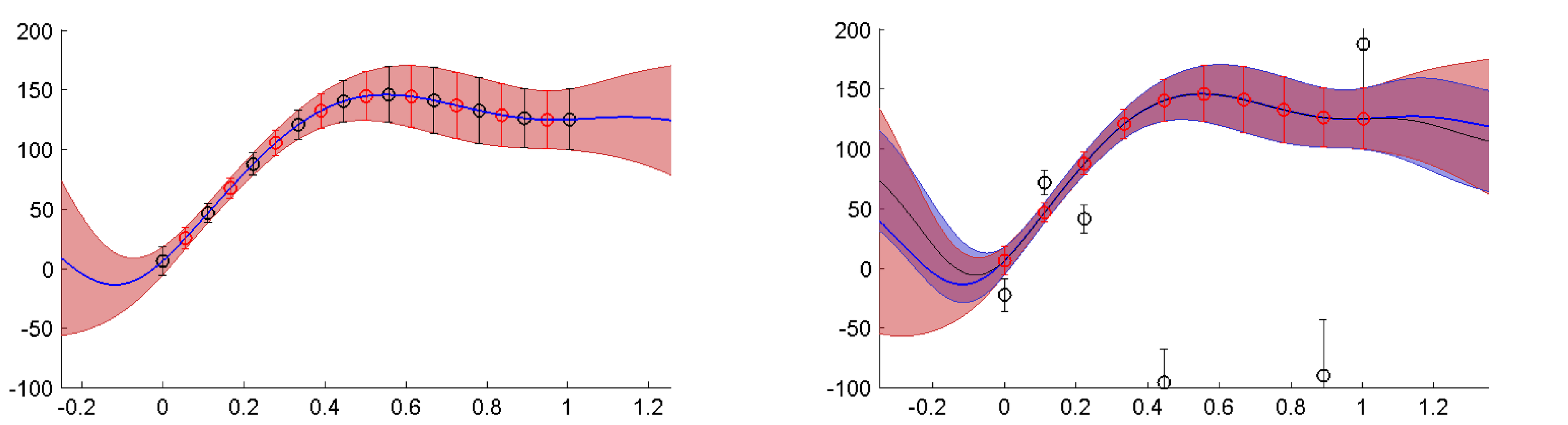


A good representation (combining GPs) of a set of trajectories is found by observing that a Gaussian process is at each point a Gaussian distribution. Combining is calculating the full Gaussian distributed population estimate of the pointwise Gaussian distributed population estimated of each trajectory at each time point. Splitting and merging GPs is supported by this technique.

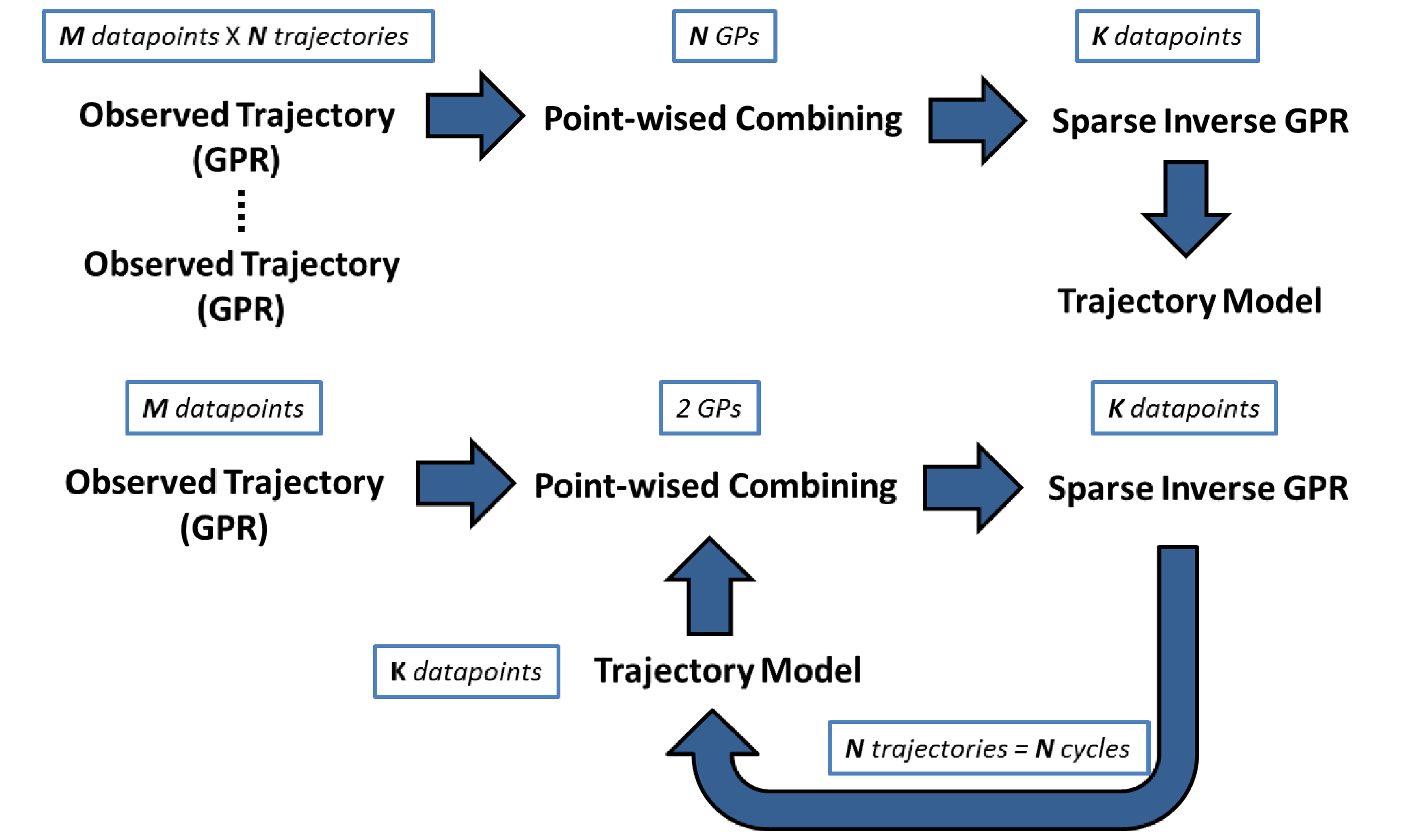
Inverse Gaussian Process Regression

Given a measurable GP posterior with unknown data/parameters, recover an artificial data set with individual observation noise and hyper parameters which provide a GP posterior approximating the unknown GP posterior.

- We present an efficient & accurate method for *sparse inverse Gaussian process regression* (SiGPR). (Sparse in the artificial data set).
- Assumption: Measured and artificial data points are on a grid.



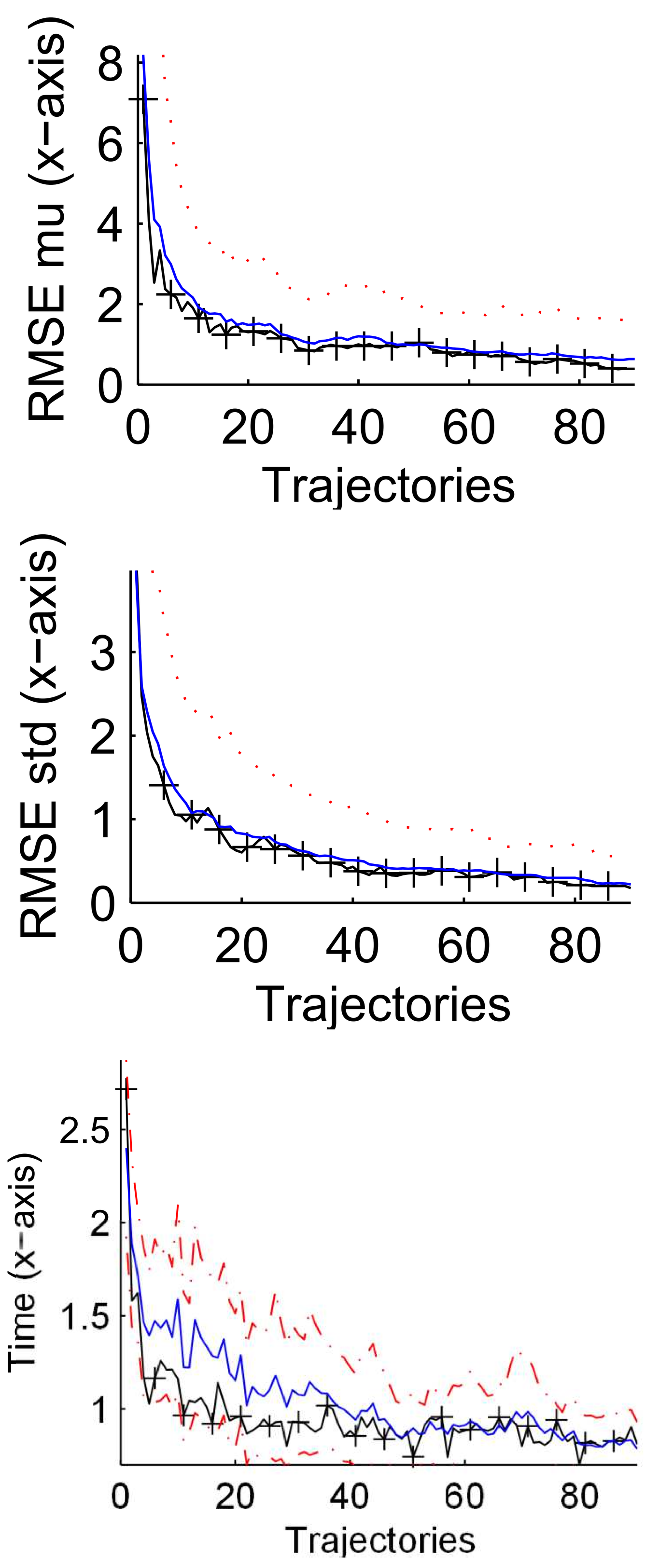
Batch & Online Algorithms

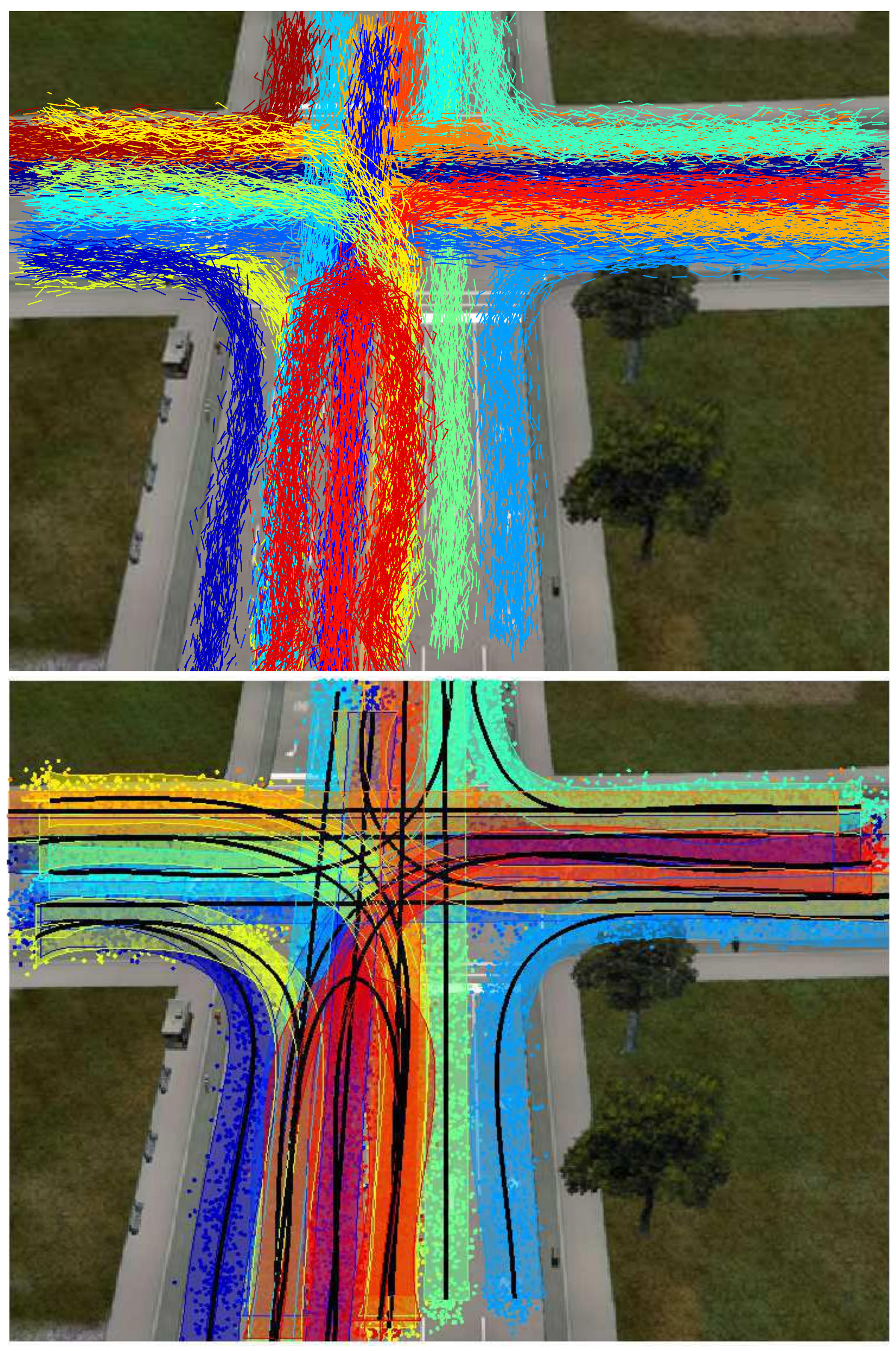


	With regular GP	With sparse GP	
Batch learning	$\mathcal{O}(NM^3 + K^3)$	$\mathcal{O}(NMP^2 + K^3)$,	$P \leq M$
Online learning	$\mathcal{O}(N(M^3 + K^3))$	$\mathcal{O}(N(MP^2 + K^3))$,	$P \leq M$

Evaluation and Results

The batch and online algorithms are evaluated on the CROSS [2] data set. 19 different trajectory classes, 90∼100 trajectories of each class with 1028∼2040 data points each. The online algorithm converges towards the batch algorithm and the learning time per trajectory decreases as more trajectories are learned. Our approach support advanced incremental modeling.





References

[1] K. Kim, D. Lee, and I. Essa. Gaussian process regression flow for analysis of motion trajectories. In *Proc. ICCV*, 2011.

[2] B.T. Morris and M.M. Trivedi. Trajectory learning for activity understanding: Unsupervised, multilevel, and long-term adaptive approach. *IEEE Tran. PAMI*, 33(11):2287–2301, 2011.

[3] M. Schneider and W. Ertel. Robot learning by demonstration with local Gaussian process regression. In *Proc. IROS*, 2010.

[4] Mattias Tiger and Fredrik Heintz. Online sparse Gaussian process regression for trajectory modeling. In *Proc. FUSION*, 2015.