Technische Universität Braunschweig

Institut für Akustik und Dynamik

Advanced Gaussian processes for efficient probabilistic machine learning

Student research project / Master thesis

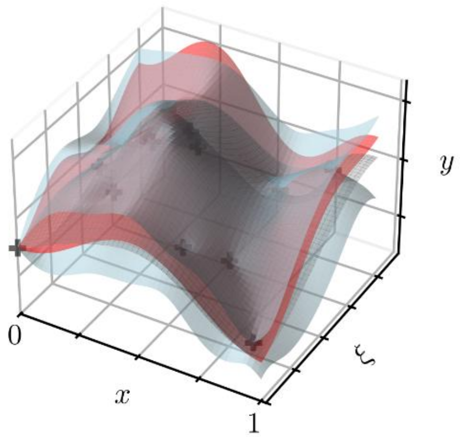
Data-driven engineering is gaining momentum due to the availability of sensor data and advances in data processing technology. Gaussian processes are powerful probabilistic machine learning models that emulate complex physical systems, allowing to fuse multiple information sources, e.g. governing equations, physical constraints or data. The GP framework is based on Bayesian inference and thus allows to quantify the uncertainty in the model prediction. Despite these strength there are still some limitation in the GP framework considering scalability to large training data sets and high dimensional problems. These limitations shall be addressed in this thesis by investigating novel approaches from the literature. The approaches will be tested on analytical as well as numerical benchmark models.

Requirements:

- Basic knowledge in probability theory, preferably Gaussian process regression
- Good programming skills
- Willingness to perform a theoretical work with focus on simulation methods

Tasks:

- Demonstrate limitations of classical GPs on a analytical benchmark example
- Implement embedded dimensionality reduction within the GP framework [1]
- Implement sparse GPs to handle large training data sets [2]
- Application and evaluation of the improvements on benchmark models



[1] Tripathy et. al. „Gaussian processes with built-in dimensionality reduction“ 2016

[2] Snelson et.al. "Sparse Gaussian processes using pseudo-inputs." 2006

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