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B A C H E L O R   T H E S I S / M A S T E R ' S   T H E S I S
for
Student's name
Student ID 0815, Degree EI

Error Bounds for Gaussian Process Regression with Compactly Supported Kernels

Problem description:

Gaussian process regression [2] is a supervised machine learning method which gains increasing attention in control and robotics research. It exhibits the advantageous property that its learned model comes with a measure for its uncertainty. However, Gaussian process regression suffers from high computational complexity which prevents its application for large scale data sets.

A possible solution to this issue is the use of compactly supported kernels in Gaussian process regression as shown e.g. in [1]. Compactly supported kernels lead to sparse covariance matrices, which can be inverted efficiently even for large data sets. This efficiency comes at the price of theoretical guarantees: standard regression error bounds in [3] cannot be directly applied to compactly supported kernels. Nevertheless, the related field of interpolation has rigorously analyzed those kernels already [4].

Therefore, the goal of this work is to exploit results from interpolation theory and apply them to Gaussian process regression with compactly supported kernels. Furthermore, compactly supported kernels are integrated into existing Gaussian process regression frameworks and their performance is compared to state of the art methods.

Tasks:

- Literature research on Gaussian process regression with compactly supported kernels
- Regression error analysis using methods from reproducing kernel Hilbert spaces
- Integration of compactly supported kernels into Gaussian process frameworks

Bibliography:

[1] Ananth Ranganathan, Ming Hsuan Yang, and Jeffrey Ho. Online sparse gaussian process regression and its applications. *IEEE Transactions on Image Processing*, 20(2):391–404, 2011.

[2] Carl E. Rasmussen and Christopher K. I. Williams. *Gaussian processes for machine learning*. The MIT Press, 2006.

[3] Niranjan Srinivas, Andreas Krause, Sham M. Kakade, and Matthias W. Seeger. Information-theoretic regret bounds for Gaussian process optimization in the bandit setting. *IEEE Transactions on Information Theory*, 58(5):3250–3265, 2012.

[4] Holger Wendland. *Scattered Data Approximation.* Cambridge University Press, 2005.

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