



## Machine learning assisted Fiber Bragg Grating based temperature sensing

Djurhuus, Martin Søren Engmann; Werzinger, Stefan; Clausen, Anders; Zibar, Darko

*Published in:*  
IEEE Photonics Technology Letters

*Link to article, DOI:*  
[10.1109/LPT.2019.2913992](https://doi.org/10.1109/LPT.2019.2913992)

*Publication date:*  
2019

*Document Version*  
Peer reviewed version

[Link back to DTU Orbit](#)

*Citation (APA):*  
Djurhuus, M. S. E., Werzinger, S., Clausen, A., & Zibar, D. (2019). Machine learning assisted Fiber Bragg Grating based temperature sensing. *IEEE Photonics Technology Letters*, 31(12), 939-942.  
<https://doi.org/10.1109/LPT.2019.2913992>

---

### General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

# Machine learning assisted Fiber Bragg Grating based temperature sensing.

Martin S.E. Djurhuus<sup>1,2</sup>, Stefan Werzinger<sup>2</sup>, Bernhard Schmauss<sup>2</sup>, Anders T. Clausen<sup>1</sup> and Darko Zibar<sup>1,2</sup>

<sup>1</sup> Department of Photonic Engineering, Technical University of Denmark,

<sup>2</sup> Institute of Microwaves and Photonics, Friedrich-Alexander University Erlangen-Nürnberg

**Abstract**—This paper proposes an alternative approach to the signal processing of temperature measurements based on Fiber Bragg Gratings (FBG) using the machine learning tool Gaussian Process Regression (GPR). Experimental results show that for a majority of the cases under consideration the reported technique provides a more accurate calculation of the temperature than the conventional methods. Furthermore, the GPR can give the uncertainty of an estimate together with the estimate itself, which for example is useful when it is important to know the worst case scenario of a measurand. GPR also has the potential to improve the measurement speed of FBG based temperature sensing compared to current standards.

**Index Terms**—Machine learning, Gaussian processes, Optical fiber sensors, Bragg gratings

## I. INTRODUCTION

Fiber Bragg gratings (FBG) are known for their uses for sensing measurands such as strain, temperature, vibration and chemical effects [1], [2]. This popularity is due to them being passive sensors, having high immunity to electrical interference and the ability to multiplex several sensors in the same fiber, which makes them attractive for several applications. Like temperature monitoring of power plants and turbines where the electrical interference is a problem [3].

In order to realize a practical sensing system using this technology, the small shift in Bragg wavelength caused by the measurand has to be detected. Most of the conventional ways of doing this uses peak tracking methods [4]. These methods can be categorized into the [4]:

- Direct method, where the peak is found without processing the shape of the reflection spectrum.
- Curve fitting method, where the FBG spectrum is interpolated with some function.
- Correlation-based method, where the correlation between the measurement and a reference gives the shift directly.
- Transform-based method, where the analysis is moved from the original domain to an alternative domain.
- Optimization-based technique, where a model is optimized to the data.

Some interesting properties of these methods are that the direct and curve fitting methods work well for fast interrogation, and the correlation-based methods are very robust to noise [4]. However, the detection accuracy of these methods is limited especially where the FBG spectrum has few sample points. This regime is useful to make faster interrogation as the measurement takes less time. Other signal processing methods, e.g., Karhunen-Loeve transform based algorithms [5], have been proposed to improve the detection accuracy in this regime, but these methods are intrinsically limited to

a small spectral range, computational intensive and have low tolerance to spectral deformations of the FBG [4].

This paper is an extension of [6] in which more data has been acquired to create a plot of the prediction error as a function of resolution for the different examined methods. Furthermore, the methods were tested for a setup using a spectrometer instead of an optical spectrum analyzer to achieve a significantly reduced number of sample points.

In this paper, we introduce the optimization-based supervised machine learning technique Gaussian Process Regression (GPR) to be used as a tool to identify the temperature from the reflection spectrum of a FBG. A significant advantage of the proposed method is that a direct mapping between the FBG spectrum and the temperature is learned, and the number of sample points should therefore to a certain extent be inconsequential. Finally, the method does not only provide an estimate but also the uncertainty of the estimate, which is a unique property of the method itself [7].

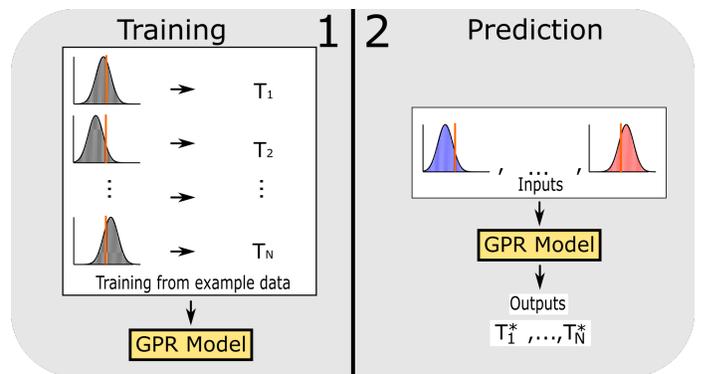


Fig. 1. Overview of the GPR method that shows how the data, in the form of multiple spectra, is given to the GPR and the temperature  $T$  for each spectrum is predicted from a model trained from example data. The orange bar is used to emphasize the shift of the spectrum, and the \* signify predicted values.

## II. FIBER BRAGG GRATING BASED SENSORS

FBGs are structures that reflect only specific wavelengths of light while transmitting the rest of the spectrum. The center of the reflected wavelengths is called the Bragg wavelength and is for a uniform structure determined by the Bragg condition [1], [2]:

$$\lambda_B = 2n_{eff}\Lambda \quad (1)$$

where  $n_{eff}$  is the effective index and  $\Lambda$  is the period of the grating. These structures can be used as sensors due to the center wavelength's dependency on temperature, which causes a shift in the center wavelength that to a linear approximation is given by [1]–[3], [8] :

$$\Delta\lambda_B = \lambda_B(\alpha + \eta)\Delta T \quad (2)$$

where  $\Delta T$  is the temperature change,  $\alpha$  is the thermal expansion coefficient,  $\eta$  is the thermo-optic coefficient and  $\Delta\lambda_B$  is the shift in Bragg wavelength. The shift is also related to other effects such as strain, which in this case is assumed unchanged. In this way if two spectra from a FBG are compared, the temperature change can be derived from the shift in the Bragg wavelength. In this work, steps are taken to minimize the strain changes.

### III. GAUSSIAN PROCESS PRINCIPLE OF OPERATION

GPR is a supervised machine learning method, which can be thought of as an alternative method of fitting a function. However, whereas other fitting methods require choosing a particular function class (e.g. polynomials) to fit after, the GPR does not [7]. Instead, the GPR mapping focuses on the relation that points have with each other through a measure of similarity called the kernel. The kernel is concretely an analytical expression that assigns a value to the Euclidean distance between two inputs, which can be vectors [7].

The procedure of using a GPR model starts with the acquisition of a training data set, which in the considered case is the reflection spectra and temperatures as shown in Figure 1. This set should be organized into a collection of input values and the corresponding outputs or targets. For the considered case, the inputs would be reflection spectra, and the targets would be measured temperatures. An expression for the kernel is chosen to express the similarity between different inputs. This choice depends on the data, but one of the commonly used ones are the squared-exponential, which is used due to its universal approximation capabilities [7].

$$k(\mathbf{x}_i, \mathbf{x}_j) = \theta \exp\left(-\frac{|\mathbf{x}_i - \mathbf{x}_j|^2}{2\beta^2}\right) \quad (3)$$

Here  $\mathbf{x}_{i,j}$  are two reflection spectra and  $\beta$  and  $\theta$  are hyperparameters of the kernel, which is optimized to each data set. However to do this, predictions need to be made. The objective of a prediction is to calculate the target value from the inputs, in this case the temperatures from the reflection spectra. The process of making a prediction first calculates the four covariance matrices, which describes how the points in the training set are related to each other, using the chosen kernel:

$$\begin{aligned} \mathbf{K} &= k(\mathbf{x}_{1:N}, \mathbf{x}_{1:N}) & \mathbf{K}_* &= k(\mathbf{x}_{1:N}, \mathbf{x}_*) \\ \mathbf{K}_*^T &= k(\mathbf{x}_*, \mathbf{x}_{1:N}) & \mathbf{K}_{**} &= k(\mathbf{x}_*, \mathbf{x}_*) \end{aligned} \quad (4)$$

where  $\mathbf{x}_{1:N}$  is the inputs of the training data and  $\mathbf{x}_*$  is the inputs of the target, that is to be predicted. Using the matrices, a prediction can be calculated:

$$\begin{aligned} y_* &= \mathbf{K}_*^T (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \mathbf{y} \\ \text{Var} &= \mathbf{K}_{**} - \mathbf{K}_*^T (\mathbf{K} + \sigma^2 \mathbf{I})^{-1} \mathbf{K}_* \end{aligned} \quad (5)$$

Here  $y_*$  is the predicted target (temperature),  $\mathbf{y}$  is the training data targets,  $\text{Var}$  is the variance of  $y_*$  representing the uncertainty,  $\sigma$  is a hyperparameter related to the noise in the data and  $\mathbf{I}$  is the identity matrix. For more details see [7].

The prediction can then be used to optimize the hyperparameters in this case  $\theta$ ,  $\beta$  and  $\sigma$  by minimizing the prediction error on the training data i.e. the error between the predicted temperatures and the measured ones. The optimization can

for example be done using a grid search where different values of the hyperparameters are attempted, and the ones that minimizes the prediction error on the training data most are used. After the optimization of the hyperparameters, the best ones are used, and the same procedure can be used to predict/calculate the temperatures for given reflection spectra. This process is summarized in Figure 1.

Finally, to see how well the created GPR model generalizes the mapping and make sure it does not overfit [9] to the training data a test is made. The process is to use test data from the modelled process, which has not been used for training, and predict the targets. The test error can be found in the same way as the training error except for using the test data. If this error is sufficiently low, then a satisfactory model has been made. Afterwards, it can be used as any other fitted model but with the additional information about the uncertainty of the estimated value, which is useful when the worst case scenario of a measurement is important.

### IV. DATA COLLECTION

The setup used for temperature measurements is shown in Figure 2. The optical path goes from an Erbium-Doped Fiber Amplifier (EDFA) connected to the first arm of a three armed circulator whose second arm is connected to the Device Under Test (DUT). The DUT contained two FBGs and was looped to control the temperature of both FBGs at the same time. The last arm of the circulator is connected to an Optical Spectrum Analyzer (OSA) that measures the light reflected from the FBGs. The temperature was changed using a Thermo-Electric Controller (TC) connected to Peltier modules placed between a heat sink and a holder wherein the FBGs were placed. This holder consisted of a bottom plate of aluminium to facilitate thermal contact with the Peltier modules. The top part consisted of a rubber plate attached to an aluminium plate that could be screwed on on-top of the fiber. The rubber plate was supposed to budge to prevent the strain of the FBG from changing too much, but could not prevent strain changes completely.

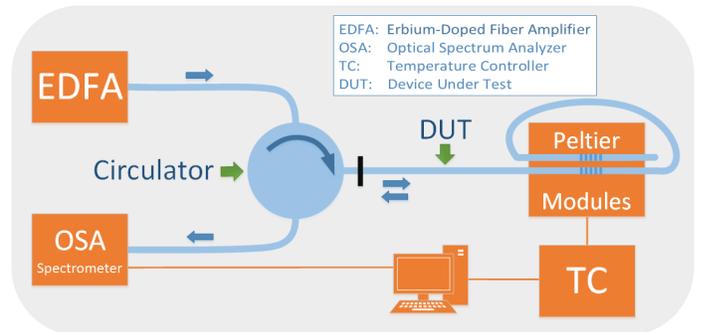


Fig. 2. Sketch of the experimental setup used to acquire data for the temperature measurements.

The power of the EDFA was set to -2 dBm limited by the spectrometers maximum input power of -22 dBm. The temperature was configured to change from 10 to 80 °C, due to limitations of the equipment, in steps of 1 °C and at each temperature step, 10 measurements of the spectrum were made using the OSA. This was done for two different FBGs

in the same fiber. FBG 1 had a Bragg wavelength around 1536.6 nm and FBG 2 around 1540.6 nm at 25 °C. The spectrum measurements obtained are the data sets that are used to perform the training and testing of the GPR as shown in Figure 1.

These measurements were taken with the resolution of the OSA set to 0.01, 0.02, 0.05, 0.10, 0.20, 0.50 and 1.00 nm. The amount of sample points for each of these resolutions were 500, 250, 100, 50, 33, 33, 33 points/nm for the ANDO AQ6317 used. The measurements were also made using a spectrometer instead of the OSA to see if the method works for even fewer points. This changes the amount of sample points from around 33 to around 6 points/nm. The spectrometer used was the Ibsen Photonics I-MON 512 USB with an optical resolution of 0.31 nm.

## V. DATA PROCESSING

As for the data processing, the goal is to learn the direct mapping between the spectrum of a FBG and the temperature as shown in Figure 1. The first step was to take the spectra extracted from the OSA and cut off a part of each to focus on a single FBG. They were then normalized to their peak value to remove the effects of differences in amplitude.

The training data inputs were the resulting spectra for 9 measurements for each temperature between 10 and 80 °C. For the training of the GPR and neural network, these were used with training targets of the temperature measured by the TC. For the centroid, the Gaussian fit and the correlation the spectra was used to find the shifts between the data and a reference. These were then used together with the measured temperature to find the slope of the temperature/shift relation. As a note here, this means that if there are strain changes that are linear with the temperature change these will be included in this slope, which can misrepresent these methods.

For the test data, the last unused reflection spectrum for each temperature integer between 20 and 70 °C of the same FBG were used as the inputs to get the methods to predict the temperature. The temperature range was limited for the test due to temperature instabilities near the edges of the range.

The standardized mean squared error (SMSE), which is the mean squared error  $\frac{1}{N} \sum_{i=1}^N (|y_{True_i} - y_{Predict_i}|^2)$  of the targets divided by the variance of the targets, was also calculated for each set of test data and used as a quality measure for the model. Here  $y_{True_i}$  and  $y_{Predict_i}$  are the measured and predicted temperature.

## VI. RESULTS AND DISCUSSION

The results of the OSA measurements are shown for FBG 1 for a resolution of 0.01 nm in Figure 3 and 4. Here the results from the GPR method, the centroid, the Gaussian fit, the correlation and a feedforward neural network with 1 hidden layer of 4 nodes are compared to show how well the proposed method performs. These specific methods are chosen as they each represent different common modelling techniques used in FBG spectrum analysis [4]. It should be mentioned that for the neural network 1 hidden layer with up to 20 nodes was tested with no improvement in performance. The SMSE for each method is stated by the plots. For each method the measured

(Red) and predicted (Blue) values are plotted as a function of the measured values. This means that the red curve is the ideal, and the blue is the actual predictions from the corresponding model. The gray area in Figure 4 is the uncertainty of the estimated value, which is only available for the GPR method.

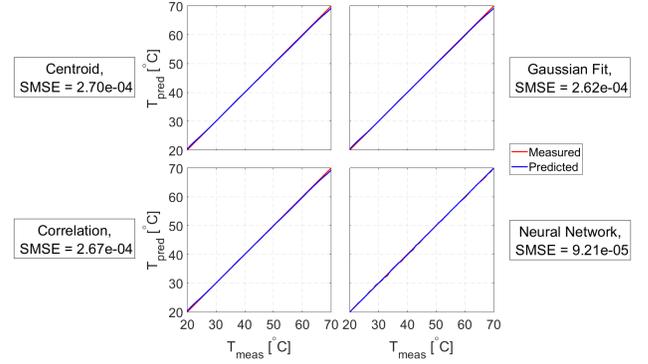


Fig. 3. Comparison between temperature prediction results of the centroid, the Gaussian fit, the correlation and the neural network methods for FBG 1 using the OSA with 0.01 nm resolution.

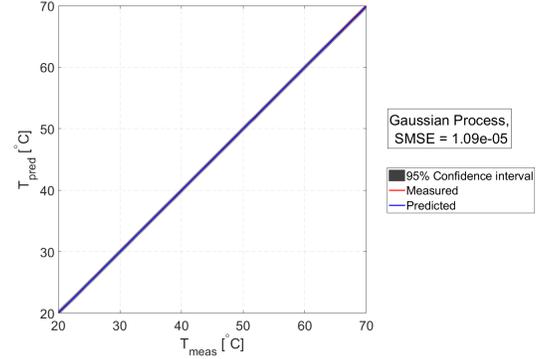


Fig. 4. Comparison between temperature prediction results of the GPR method for FBG 1 using the OSA with 0.01 nm resolution.

Figure 3 and 4 show that the Gaussian process can learn the direct mapping between the spectra and temperature, and it has a performance comparable to the conventional methods. It can also be seen that the centroid, the Gaussian fit and the correlation has very similar performances while the neural network and GPR method performs better. The reason for the low error of the "data-driven" methods is probably that the training and test data are very similar. This shows that because these methods do not follow a physical model like the other methods, they do get to ignore some error sources that other methods have to deal with. This can be an advantage for end-users, who do not care about the model itself. Another interesting observation is the confidence interval that can vaguely be seen in the GPR results. More quantitative results are found by investigating the effect the resolution has on the results.

This investigation is done using the OSA at different resolutions, repeating the earlier mentioned modellings and collecting the SMSE from each FBG, for each temperature and for each of the 10 measurements of the spectra. The median of the collected SMSEs with the standard deviation is plotted as a function of resolution for the different methods

on a logarithmic scaled graph. This is shown in Figure 5. Here a low error with a low standard deviation would be the best result.

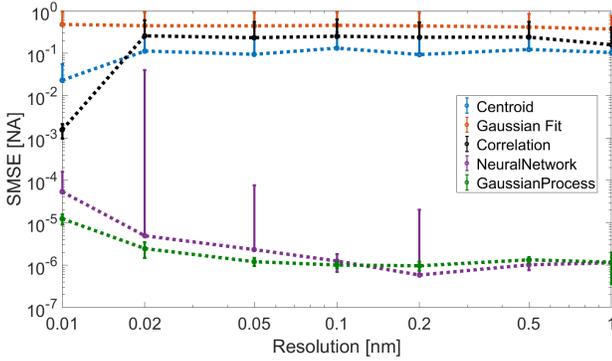


Fig. 5. Comparison between temperature prediction results of the centroid, the Gaussian fit, the correlation, the neural network and the GPR methods with the model error plotted for different resolutions for both of the FBGs using the OSA.

The results of the resolution investigation in Figure 5 show that the GPR and neural network method have the lowest error. It can also be seen that the error of these methods is going down with a coarser resolution, which is possibly due to noise going down as the aperture in the OSA is opened. An advantage of the GPR is that standard deviation in most cases are lower than the neural network. Therefore, in general the GPR method handles resolution better than the other methods as seen by comparing the SMSE plots. This is a promising feature of the method, but the lowest number of sample points using the OSA is 33 points/nm so an instrument with even fewer sample points was used.

These results for FBG 1, using a spectrometer which has 6 points/nm, is shown in Figure 6 and 7. These are found using the same methods as for Figure 3 and 4.

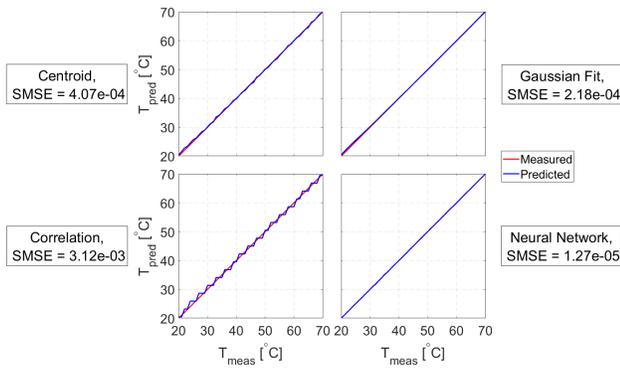


Fig. 6. Comparison between temperature prediction results of the centroid, the Gaussian fit, the correlation and the neural network methods for spectrometer results for FBG 1.

Figure 6 and 7 show that the GPR method performs the best with a low SMSE. So the GPR method also works when the amount of sample points are very low. This regime is interesting as it allows for fewer restrictions on the interrogator, which could make the system cheaper and allows for faster measurements. For example, a measurement with the range 1510 to 1590 nm takes 175.6 s with the OSA with a resolution

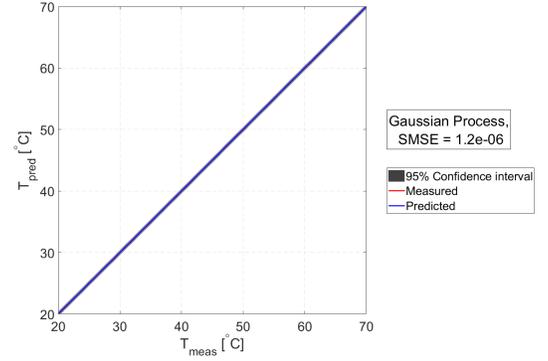


Fig. 7. Comparison between temperature prediction results of the GPR method for spectrometer results for FBG 1.

of 0.05 nm and 11.3 s with the spectrometer. The duration of the algorithms for both training and testing with a 639x3001 training set and 71x3001 test set are GPR 1.14 s, centroid 0.03 s, Gaussian fit 19.61 s, correlation 0.24 s and neural network 1028.23 s. So the GPR does not add a lot of extra time compared to the other methods.

## VII. CONCLUSION

It has been shown, that the GPR can learn the direct mapping between the reflected spectra and temperature, and in most of the cases under consideration it even outperforms conventional methods with a lower error and a higher detection accuracy. Furthermore, the GPR can give the uncertainty of an estimate together with the estimate itself, which for example is useful when it is important to know the worst case scenario of a measurand. Finally, the GPR method has the potential to be used with only very few samples per spectrum allowing for faster measurements.

## REFERENCES

- [1] A. Kersey, M. Davis, H. Patrick, M. LeBlanc, K. Koo, C. Askins, M. Putnam, and E. Friebele, "Fiber grating sensors," *Journal of Lightwave Technology*, vol. 15, no. 8, pp. 1442–1463, 1997. [Online]. Available: <http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=618377>
- [2] A. Othonos, "Fiber Bragg gratings," *Citation: Review of Scientific Instruments*, vol. 68, no. 4309, 1997. [Online]. Available: <https://doi.org/10.1063/1.1148392> <http://aip.scitation.org/toc/rsi/68/12>
- [3] M. M. Werneck, R. C. S. B. Allil, B. A. Ribeiro, and F. V. B. de Nazaré, "A Guide to Fiber Bragg Grating Sensors," in *Current Trends in Short- and Long-period Fiber Gratings*. InTech, may 2013. [Online]. Available: <http://www.intechopen.com/books/current-trends-in-short-and-long-period-fiber-gratings/a-guide-to-fiber-bragg-grating-sensors>
- [4] D. Tosi, "Review and Analysis of Peak Tracking Techniques for Fiber Bragg Grating Sensors," *Sensors*, vol. 17, no. 10, pp. 1–35, 2017. [Online]. Available: <http://www.mdpi.com/1424-8220/17/10/2368>
- [5] J. Hervas, D. Tosi, H. Garcia-Miquel, D. Barrera, C. R. Fernandez-Pousa, and S. Sales, "KLT-Based Interrogation Technique for FBG Multiplexed Sensor Tracking," *Journal of Lightwave Technology*, vol. 35, no. 16, pp. 3387–3392, aug 2017. [Online]. Available: <http://ieeexplore.ieee.org/document/7575720/>
- [6] M. S. Djurhuus, S. Werzinger, B. Schmauss, A. T. Clausen, and D. Zibar, "Machine learning assisted Fibre Bragg Grating based temperature sensing," in *26th International Conference on Optical Fiber Sensors*. OSA, sep 2018, p. 4. [Online]. Available: <https://www.osapublishing.org/abstract.cfm?URI=OFS-2018-ThE80>
- [7] C. E. Rasmussen and C. K. I. Williams, *Gaussian processes for machine learning*. MIT Press, 2006. [Online]. Available: <http://www.gaussianprocess.org/gpml>
- [8] T. Zeh, "Optical Fiber Bragg Sensors-Measurement Systems and Signal Processing," Ph.D. dissertation, Technischen Universität München, 2004.
- [9] C. M. Bishop, *Pattern Recognition and Machine Learning*, 2013.