| Popular science summary of the PhD thesis | |
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| PhD student | Martin Jørgensen |
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| Title of the PhD thesis | Stochastic Representations with Gaussian Processes and Geometry |
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| PhD school/Department | Mathematics, Physics and Informatics / DTU Compute |
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| Science summary | |
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| Machine learning tasks often require providing some connection between inputs and outputs. Dependent on the task such relationships are modelled with neural networks or Gaussian processes. The uncertainty linked with this relationship is crucial, both for down-stream tasks and decision making but also occasionally for the system's advancements. In this thesis, I study this uncertainty in various ways. For the neural network setting, we present a toolbox for training and estimating variance networks, which are networks specifically designed to handle variation.  For Gaussian processes, we study stochastic differential equations and their diffusions as a building block for various machine learning tasks, such as dynamical modelling and regression. By molding the diffusions with Wishart processes, we design it all in a Bayesian non-parametric and semi-parametric way.  In unsupervised machine learning, when the input-output framework only has input, we study geometry and Gaussian processes to compress the information of the data. This task is often referred to as non-linear dimensionality reduction and we present a method whose inputs are geometric: distances between observations.  As a last note, we study bivariate causal inference, which is the task of reasoning if X caused Y or the reverse. We are particularly focusing on the ambiguity in the decision process and present a non-parametric estimator for more robustness towards a causal invariant. | |

Please email the summary to the PhD secretary at the department