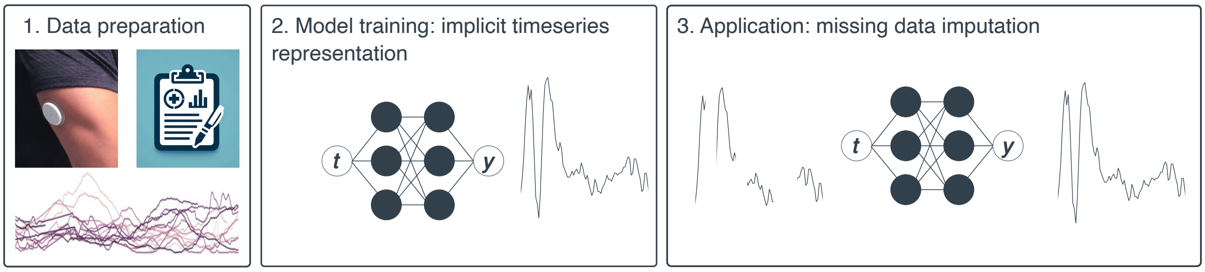
Neural implicit functions for high-resolution representation of wearable data

Background: More than 530 million patients suffer from diabetes, a leading cause of death and contributor to a host of long-term serious health complications. To manage diabetes, patients need to closely monitor their blood glucose levels. This is often done through wearable continuous glucose monitoring (CGM) devices, which provide real-time feedback patients can use to decide on insulin injections throughout the day.

Recent advances in machine learning for imaging data could in principle be readily applied to analyse these wearable timeseries. However, frequently missing values hamper the direct translation of models from other disciplines. In this project, we will investigate a novel paradigm for imputing data which is based on neural implicit functions, a popular and highly effective image reconstruction technique in computer vision.



Aim: In this project, the student will develop deep neural implicit functions for continuous (theoretically infinite resolution) time series representation, which can be applied for missing data imputation among many other relevant applications.

Materials and Methods: The student will work on a publicly available wearable dataset of continuous glucose monitoring data from people with diabetes. They will start with an existing codebase for implicit neural representation of natural images, and adopt the method to work on one-dimensional timeseries data. The student can expect to reach this first milestone quickly. They will then evaluate the developed neural field models for their ability to impute missing data on artificially corrupted data. If successful, we will then focus on naturally arising follow-up questions such as: Can we use our models for effectively improving signal quality, and if yes, does improved signal quality lead to improved performance in downstream tasks such as timeseries forecasting? Can we quantify the uncertainty of the imputed values? The student will work in a research group focused on machine learning in medicine, where we have a strong expertise in deep learning for biomedical data analysis.

Nature of the Thesis:
Literature review: 10%
Data exploration: 30%
Model development: 40%
Results analysis: 20%

Requirements:
Solid machine learning knowledge
Programming experience (Python, ideally Pytorch)
Interest/Experience with processing of high-dimensional data (e.g. wearable, timeseries, images)
Strong written and verbal communication skills

Supervisor(s):
Prof. Dr. Lisa Koch, Prof. Dr. Lilian Witthauer

Institutes: Lab for Machine Learning in Medicine

References:
Tancik, Matthew, et al. "Fourier features let networks learn high frequency functions in low dimensional domains." *Advances in neural information processing systems (NeurIPS)* (2020)
Amiranashvili, Tamaz, et al. "Learning shape reconstruction from sparse measurements with neural implicit functions." *International Conference on Medical Imaging with Deep Learning (MIDL)* (2022)

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Please attach your transcripts when you reach out. We look forward to hearing from you!