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XAI-MICROPYTHON: Explainable Artificial Intelligence with MicroPython

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Software

- Review
- Repository
- Archive

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Summary

XAI-MICROPYTHON is a MicroPython based framework which emphasizes the fundamentals of statistics, machine learning and deep learning, since they are increasingly driving innovation across various fields (LeCun et al., 2015). These fundamentals can also be transferred on microcontrollers (Ray, 2022), for educational purpose or e.g. in order to process sensor data (Cioffi et al., 2020). Since microcontrollers have limited computational resources, a particularly efficient implementation of these methods is required (Delnevo et al., 2023; Wulfert et al., 2024). However, it is the efficient implementation that provides insights into the fundamentals of statistics, machine learning and deep learning in terms of explainable artificial intelligence that makes this approach also relevant for educational purpose (Haque et al., 2023; Meske et al., 2022). Coding from scratch in MicroPython allows for a streamlined and tailored approach (Delnevo et al., 2023) and provides users with transparent insights into underlying principles and the resulting code, which makes XAI-MICOPYTHON suitable for didactic application (Collier & Powell, 2024; Scherer, 2016; Verma et al., 2022).

Target group

XAI-MICROPYTHON draws on well-known exercise data sets and common methods to give (academic) teachers a quick start in designing their own teaching materials. In addition, XAI-MICROPYTHON can of course also be used by self-learners.

Statement of need

The methods presented with XAI-MICROPYTHON can actually be easily implemented in Python using libraries such as SciKit-Learn. However, the aim of XAI-MICROPYTHON is not only to call up and apply already existing functions, but also to understand their methodological foundations via programming from scratch in MicroPython and without recourse to previous libraries (Kong et al., 2022). A previous investigation of skill requirements in artificial intelligence and machine learning job advertisements (Verma et al., 2022) served as a guide for the development of XAI-MICROPYTHON. It is intended to provide insights into basic statistical principles, some machine learning algorithms as well as the structure and functioning of neural networks as basis for artificial intelligence (Frank et al., 2020; Scherer, 2016; Schmidt et al., 2020). Since XAI-MICROPYTHON is based on the MicroPython programming language, it can be used on microcontrollers like the Raspberry Pi Pico 2 (Sakr et al., 2021) or it can be called up directly via JupyterLite as a live demo in the browser. Especially the step-by-step visibility in MicroPython helps users to identify and understand the mathematical and statistical foundations of artificial intelligence (Kong et al., 2022). This is in accordance with the primary goals of explainable

artificial intelligence (Haque et al., 2023; Schmidt et al., 2020) and provides insights into artificial intelligence related responsibilities (Collier & Powell, 2024; Frank et al., 2020) as well as practical experiences (Li et al., 2021). Therefore, XAI-MICROPYTHON shall promote necessary innovation and problem-solving skills in accordance with the scientific discourse (Verma et al., 2022).

Basic elements

XAI-MICROPYTON introduces to mean, variance, standard deviation, covariance and correlation as elements of univariate and bivariate statistics, which are necessary for the implementation of machine learning algorithms like single and multiple linear regressions. Simple classification tasks will be highlighted via multiple logistic regression, followed by k-Means as algorithm, as well as the concept of the within cluster sum of squares, for the demonstration of clustering. Furthermore, factor analysis will be implemented in MicroPython in order to demonstrate dimensionality reduction. In particular, the division into four different machine learning application areas is based on the classification of SciKit-Learn (regression, classification, clustering and dimensionality reduction). Finally, a pre-trained neural network and a self-learning neural network will be implemented in MicroPython in order to highlight some common activation functions as well as the underlying principles of layers and neurons. Therefore, XAI-MICROPYTHON is an underlying framework, which can be extended independently by (academic) teachers with further algorithms and methods and is intended to grow via the community guidelines provided.

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