Institute for Automation and Applied Informatics
Hermann-von-Helmholtz-Platz 1
76344 Eggenstein-Leopoldshafen
http://www.iai.kit.edu

Karlsruhe Institute of Technology

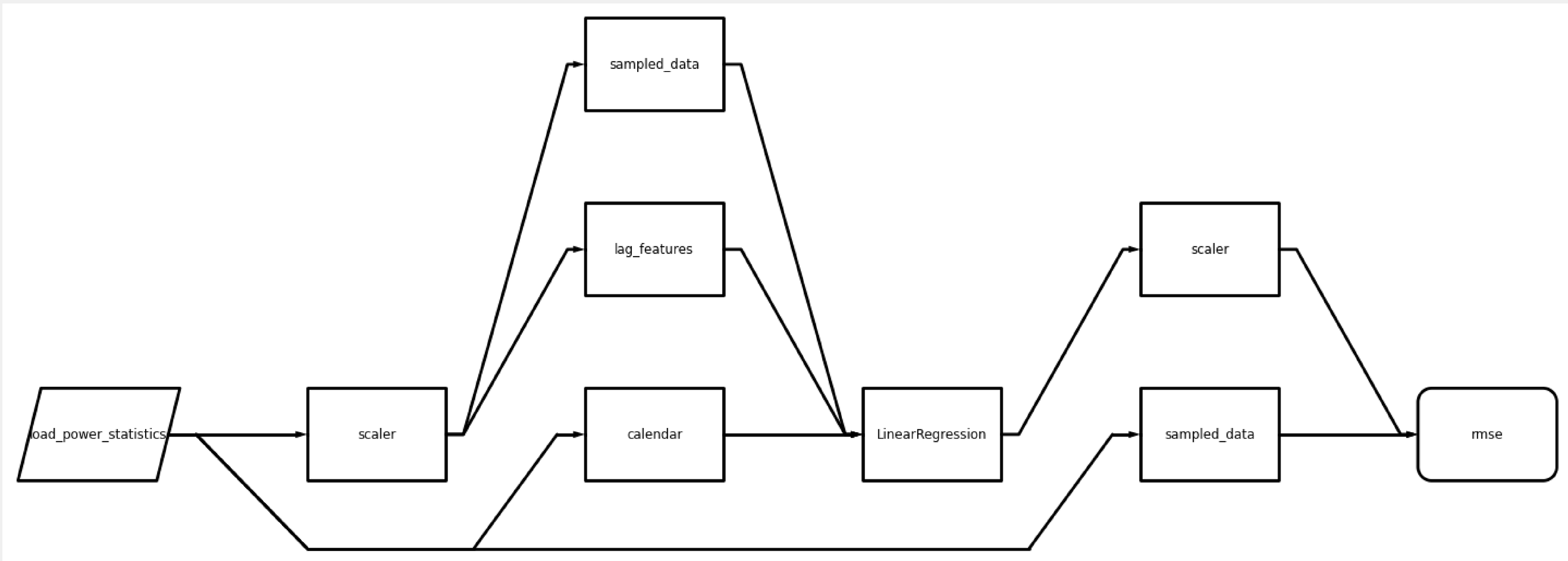
HELMHOLTZ AI
ARTIFICIAL INTELLIGENCE
COOPERATION UNIT

Applying pyWATTS to Non-Sequential Machine Learning Use Cases

Kaleb Phipps | Benedikt Heidrich |
Stefan Meisenbacher | Marian Turowski | Oliver Neumann | Veit Hagenmeyer | Ralf Mikut

Non-Sequential Pipelines for Machine Learning

pyWATTS creates non-sequential pipelines characterised by arbitrary branching and merging of data flows.

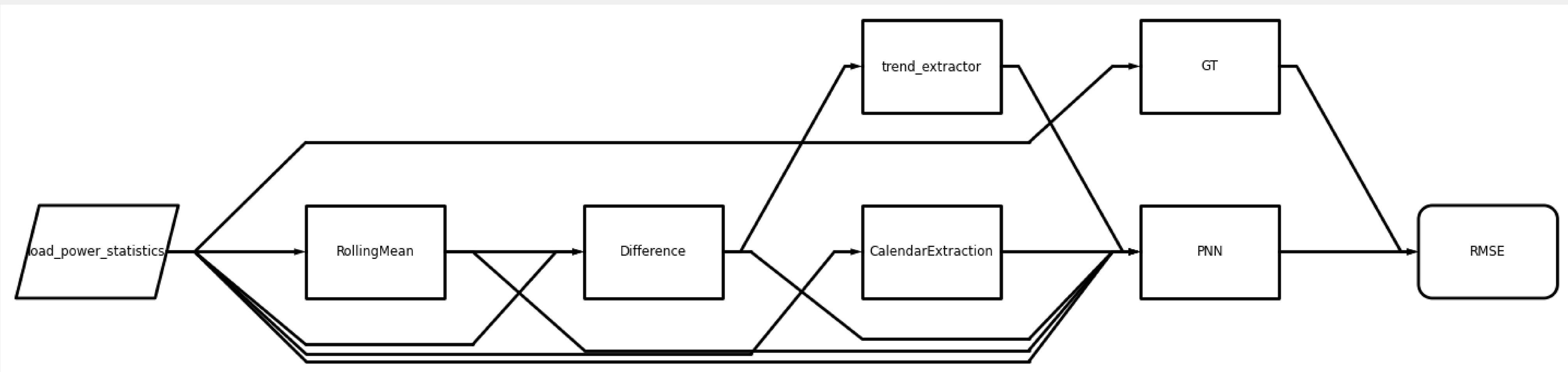


Advantages

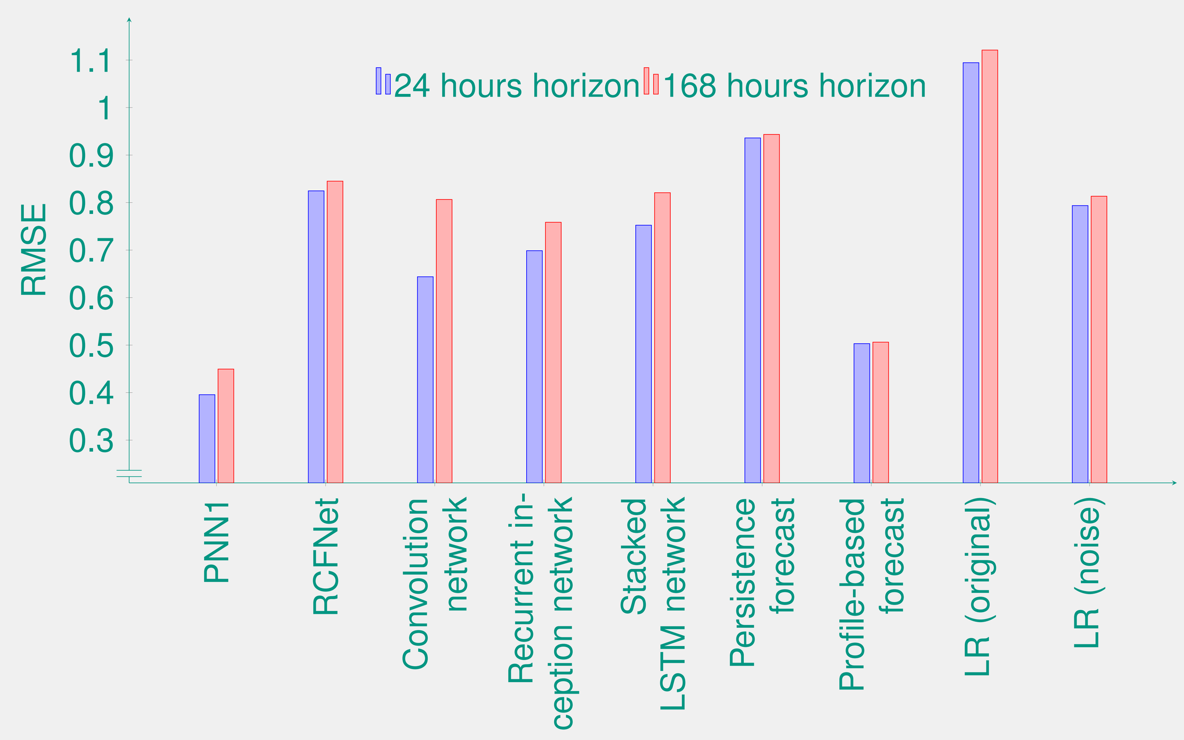
- Realise complex machine learning tasks in a single pipeline.
- Simpler code that is easier to write and intuitive.
- Fewer nested variables enable simpler hyperparameter optimisation.
- It is possible to combine multiple tasks in one single pipeline.

The Profile Neural Network (PNN) in pyWATTS [2]

Summary: Many forecasts are performed on time series data containing calendar-driven periodicities. The PNN is a deep learning-based method that explicitly considers these calendar-driven periodicities with profiles. Specifically, PNN statistically groups a time series using calendar information and then calculates statistical information, i.e. profiles, for each group separately. These profiles are combined with a deep convolutional neural network to generate a state-of-the-art forecast.

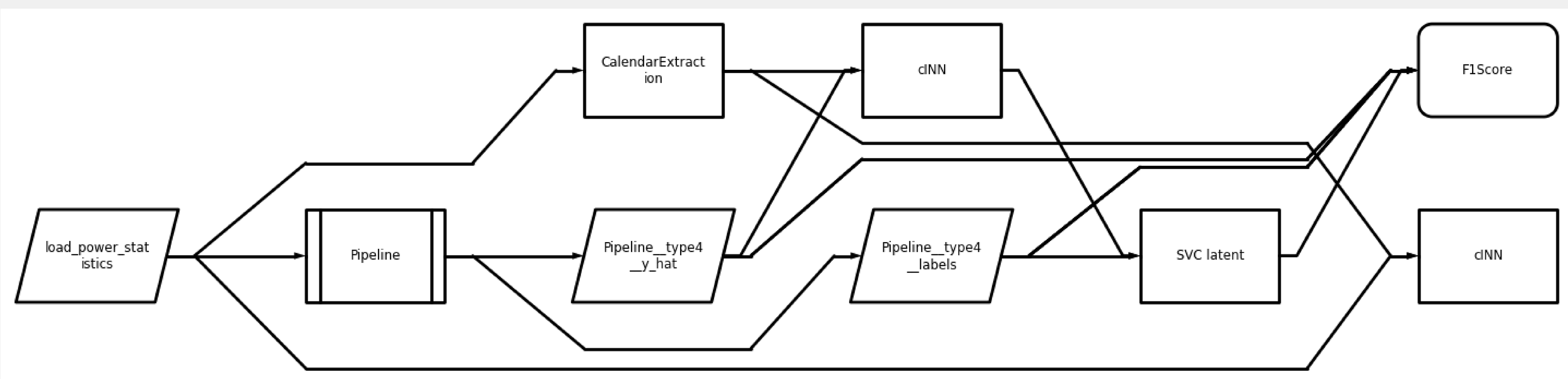


Evaluation Results

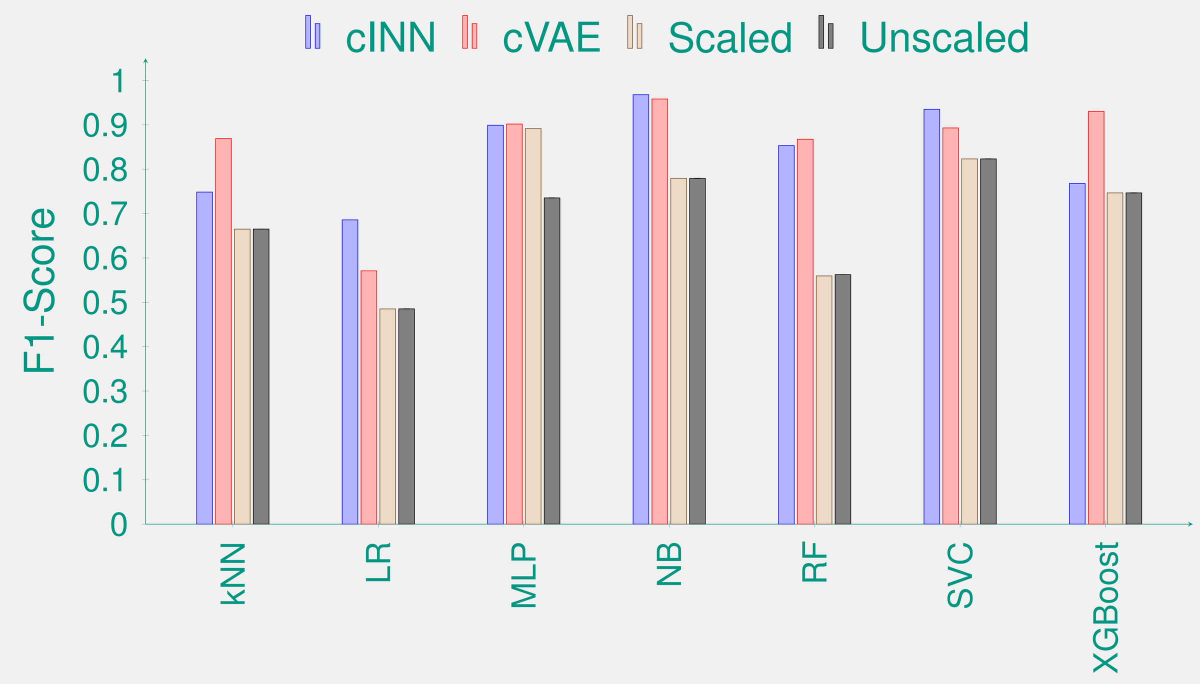


Enhancing Anomaly Detection Methods Using cINN & cVAE Latent Space Data Representations in pyWATTS [3]

Summary: Anomaly detection methods are typically applied directly to the recorded data. However, other tasks, such as forecasting, have benefited from latent space representations of this data. Therefore, we create latent space data representations of time series using generative models and directly apply existing anomaly detection methods to this representation. The evaluation shows that our approach generally improves the anomaly detection performance of the considered methods while only moderately increasing computational costs.



Evaluation Results



pyWATTS Development Roadmap

Hyperparameter tuning: The scikit-learn hyperparameter tuning functionality will also be directly available in pyWATTS pipelines.
Integration with sktime: pyWATTS' non-sequential pipelines will be made directly available in sktime, and sktime modules can be directly included in pyWATTS.
Performance optimization: pyWATTS will enable parallel execution of concurrent pipeline steps.

Kaleb Phipps – kaleb.phipps@kit.edu
Institute for Automation and Applied Informatics
Hermann-von-Helmholtz-Platz 1
76344 Eggenstein-Leopoldshafen
Germany

References

1. Benedikt Heidrich, et al. 2021. pyWATTS: Python Workflow Automation Tool for Time Series. arXiv:2106.10157.
2. Benedikt Heidrich, et al. 2020. Forecasting energy time series with profile neural networks. The Eleventh ACM International Conference on Future Energy Systems (e-Energy '20). doi: 10.1145/3396851.3397683
3. Marian Turowski, et al. 2022. Enhancing Anomaly Detection Methods for Energy Time Series Using Latent Space Data Representations. The Thirteenth ACM International Conference on Future Energy Systems (e-Energy '22). doi: 10.1145/3538637.3538851