Silesian University of Technology

Multivariate forecasting of energy consumption in CoBotAGV data

Dariusz Mrozek, Daniel Kostrzewa,
Bohdan Shubyn, Piotr Grzesik, Paweł Benecki

Department of Applied Informatics

Agenda

- Datasets
- Reminder on past research
- Current work
    - Multivariate forecasting
    - Federated Learning
- Further steps
- Research papers published

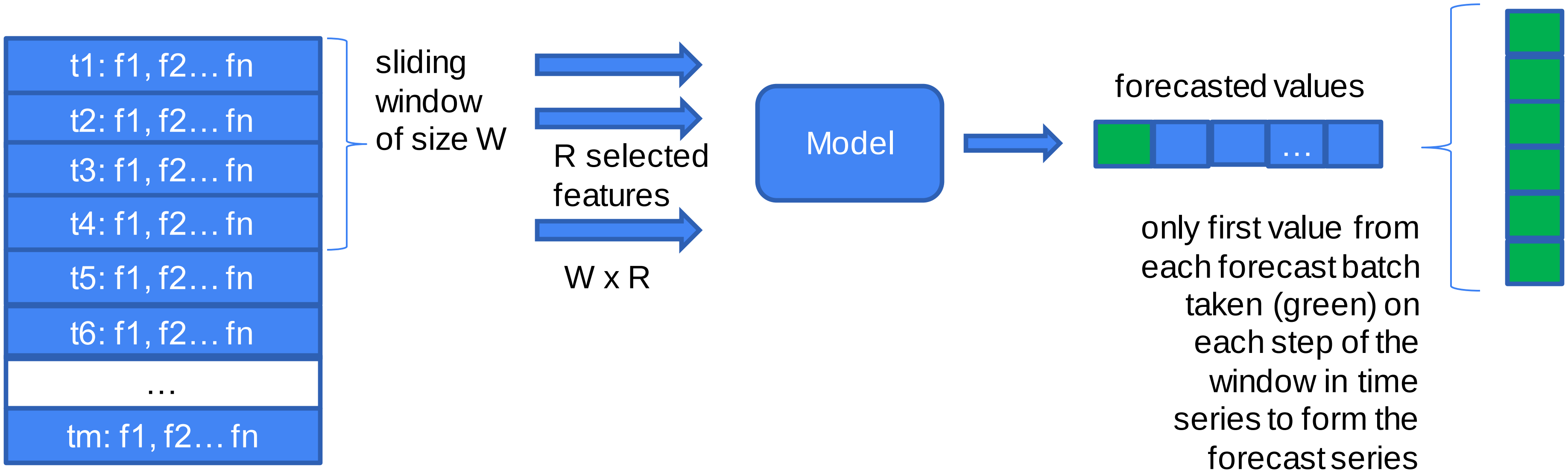
Datasets

- Formica-1 (CoBotAGV)
  - Different scenarios: straight-line runs, accelerations, retardations loaded and without any load
  - Momentary power consumption
  - Electrical, motion and status signals
  - 10 time series, without anomalies
- Husky A200
  - Robotic Unmanned Ground Vehicle platform
  - Power consumption, motion data, environmental data
  - 113 time series, without anomalies
- IEEE Battery
  - Acquired from BMW i3
  - Power consumption, vehicle data, motion data, environmental data
  - 72 time series, without anomalies

Approach to anomaly detection

- One-class classification problem (normal vs. non-normal)
- Model is fitted to normal data
- Model evaluates unseen data which results in anomaly score
- In practice, there are two stages:
  - Forecasting of signal basing on model trained on normal data
    - Using historical data
    - Univariate
    - Multivariate
  - Evaluating the error between actual and forecasted data

Multivariate forecasting scheme



Past research on forecasting of energy consumption

- Multivariate forecasting using different models
  - LSTM (Long Short-Term Memory)
  - GRU (Gated Recurrent Unit)
  - BiLSTM (Bidirectional LSTM)
  - BiGRU (Bidirectional GRU)
  - Each model was in 1- or 2-layers version
- Different sliding window sizes
- Reducing dimensionality of dataset
  - Selecting features based on correlation with energy consumption
- (agnostic of any higher level features like segments or jobs)

Results

- Forecasting of energy data using neural networks works quite effectively
- Smaller networks (GRU) perform poorer than larger (LSTM)
  - this can pose a problem while working on embedded environments
- Feature selection
  - Can improve results
  - Results in shorter processing times and smaller models
    - This can be beneficial in embedded setting

Improving forecasting

- Transformation of feature space: PCA, manifolds (Local Linear Embedding, Isomap, etc.)
  - Eliminate overfitting and non-relevant features
  - Reduce dimensionality
    - improve embedding application possibilities

- Feature selection using evolutionary algorithms

- Adding historical energy data to model input
  - This was missed in previous research
  - Possibly can be helpful with lowering voltage of battery which posed a problem in previous research

Improving forecasting

- Using more sophisticated Deep Learning models
  - SCINet [1]
  - DLinear [2]

- Evaluate also classic regression models and simple convolutional network [3]

[1] Time Series is a Special Sequence: Forecasting with Sample Convolution and Interaction, Minhao Liu, Ailing Zeng, Zhijian Xu, Qiuxia Lai, Qiang Xu, 2021
[2] Are Transformers Effective for Time Series Forecasting?, Ailing Zeng, Muxi Chen, Lei Zhang, Qiang Xu, 2022
[3] A Comparison between ARIMA, LSTM, and GRU for Time Series Forecasting, Peter T. Yamak, Li Yujian, and Pius K. Gadosey. 2019

Federated learning research

- Comparison of various training strategies
    - Splitting training data equally for nodes, retaining 10% as test set
        - E.g. for 3 nodes: 30% on each node
    - Each node's set split in halves swapped between iterations
        - E.g.: in odd iterations use the first 15%, then average weights, in even iterations use the other 15%, average weights again
    - Using whole training data as test set to improve generalization abilities

Federated learning research

- Different strategies of merging model weights

- In standard flow, a normal average is used

- We evaluate weighted averaging of model weights
  - Weight based on quality of prediction on specific node
  - Here proper choosing of test set is to be carefully examined

Federated learning research

- Using data from AGV instead of NAB
  - Each series as learning data for a separate node
  - Use the strategies above to evaluate them

- Using models evaluated during previous research, i.e. (Bi)LSTM, (Bi)GRU

Further steps

- Using the newest data from CoBot (gathering started in July)
  - Longer routes
  - Longer times
  - Longer battery unloading
  - More load scenarios (no load / half load / full load / overload)
- Introducing artificial anomalies to real energy data
  - Not a straightforward process

Papers

- Federated Learning for Anomaly Detection in Industrial IoT-enabled Production Environment Supported by Autonomous Guided Vehicles, B. Shubyn, D. Mrozek, T. Maksymyuk, V. Sunderam, D. Kostrzewa, P. Grzesik, P. Benecki, International Conference on Computational Science 2022
- (October 2022) Forecasting of Energy Consumption for Anomaly Detection in Automated Guided Vehicles: Models and Feature Selection, P. Benecki, D. Kostrzewa, P. Grzesik, B. Shubyn, D. Mrozek, International Conference on Systems, Man, and Cybernetics 2022

Multivariate forecasting of energy consumption in CoBotAGV data

Dariusz Mrozek, Daniel Kostrzewa,
Bohdan Shubyn, Piotr Grzesik, Paweł Benecki

Department of Applied Informatics