E.ON Energy Research Center
ACS | Institute for Automation of Complex Power Systems

Master Thesis:

Explainable Deep Sequence Model for Energy Forecasts

Brief Background:
The possibilities of applying machine learning (ML) concepts to forecast critical values in energy have shown immense benefits. These approaches leverage sequence-to-sequence models such as vanilla recurrent neural networks (RNN), long short-term memories networks (LSTM) e.t.c., to predict the behaviour of energy systems in the future. In other words, the models learn an input-output mapping from historical data, and are quite effective in modelling non-linear dependencies in the data. Nonetheless, ML solutions tend to be black-box models such that they do not provide perceptive information about model-encoded information nor the inputs that influence the outputs. To this end, the field of explainable Artificial Intelligence (XAI) involves methods developed to interpret the information encoded in the layers of ML models. Notwithstanding the success of XAI as detailed in [1, 2], the approaches are typically post hoc analysis with consequent computational cost.
Therefore, in this thesis, we will consider the following:

i. Designing ML models with an inbuilt mechanism for interpretability, wherein mixture density models [3] portends a promising direction.
ii. Develop and formalize a theoretically founded metric to evaluate the relevance of inputs to the model outputs.
iii. Show a proof of concept via extensive experiments on synthetic data and comparison to competing methods.
iv. Leverage the developed approaches in (i and ii) to explain the causes (in terms of the inputs) of performance degradation in common energy systems such as: solar photovoltaic system and power generation lines.

In the process, the candidate will explore interesting and advanced concepts in ML, theoretical data mining, causal inference and probabilistic ML to solve problems in the energy domain.

Your Tasks:
- Literature review on state-of-the-art sequence ML models and XAI.
- Familiarization with the keras[1] and tensorflow probability[2] frameworks for coding neural networks—the tutorials are quite detailed and easy to comprehend.
- Implement probabilistic sequence ML models i.e., ML models with uncertainty of parameter values.
- Design experiments to validate results.
- Document results scientifically as the final requirement for the thesis process.

1 https://keras.io/guides/ 2 https://www.tensorflow.org/probability/overview

Note:

Formulation of the problem is ongoing and possible directions have been identified. Thus, candidates have the freedom to explore desired concepts or make contribution to the present state of work.

Your Profile:

- Master student in computer science, electrical engineering or related fields.
- Good knowledge of RNN, LSTM and experience with neural network implementation will be beneficial.
- Knowledge of probabilistic learning such as variational inference will be beneficial.
- Interest in inter-disciplinary research topics.
- Ability to work independently and a penchant for critical thinking.

Thesis Take Away:

- Inter-disciplinary thesis where the candidate will enhance knowledge in ML, causal inference, and explainable AI.
- Practical application and hands-on experience in popular and novel ML techniques in the energy domain.
- Opportunity to contribute to scientific writing.

Required Technologies:

Python, Tensorflow or pytorch, keras, tensorflow probability.

Final Notes:

Supervision will be done in English.

Your application should include your CV and transcript. Also, feel free to make initial contact if you need clarifications about the topic.

References:

[1] Jonas Fischer, Anna Olah, Jilles Vreeken, "What's in the box? Exploring the inner life of neural networks with robust rules", *Proceedings of the 38th International Conference on Machine Learning*, PMLR 139:3352-3362, 2021

[2] Linardatos, Pantelis, Vasilis Papastefanopoulos, and Sotiris Kotsiantis. 2021 "Explainable AI: A Review of Machine Learning Interpretability Methods", *Entropy* 23, no. 1: 18. https://doi.org/10.3390/e23010018

[3] C. M. Bishop, "Mixture density networks", 1994

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