

# Transferability in NILM

A Review

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### Agenda

- The Genesis of Deep Neural NILM
- What is Transferability?
- Why is Transferability so hard to achieve?
- Latest Trends in Related Work
- Impact of NLP Breakthroughs
- Challenges

# The Genesis of Deep Neural NILM

- Introduction of DNN
  - LSTM
  - Denoising Autoencoder
- One network per target appliance
- DNNs tend to outperform FHMMs
- Training is computationally expensive
- Tests on a house not seen during training
  - Promising results (for 2015)



Kelly, Jack, and William Knottenbelt. "Neural NILM: Deep neural networks applied to energy disaggregation." In *Proceedings of the 2nd ACM international conference on embedded systems for energy-efficient built environments*, pp. 55-64. 2015.

# What is Transferability?

- In Machine Learning, a dataset is split into:
  - Training set is used to train the neural network
  - Test set serves to evaluate the accuracy of the neural network
- The elephant in the room: overfitted neural networks
- A definiton of Transferability:
  - "The ability to produce accurate results on a house that is not present in the training set"



Huber, Patrick, Alberto Calatroni, Andreas Rumsch, and Andrew Paice. "Review on deep neural networks applied to low-frequency nilm." *Energies* 14, no. 9 (2021): 2390.

# Transferability of Neural Networks

- How do neural nets handle unknown appliances?
- Can DNN support a scalable NILM roll-out?
- Issues with handling unknown appliances:
  - Duty cycles
  - Power consumption levels
  - Noise in aggregate data (smart meter data)
- Neural networks based on:
  - Convolutional Neural Net (CNN)
  - Gated Recurrent Units (GRU)
- Learnings:
  - · Significant reduction in model complexity
  - Proven ability to transfer across datasets



REDD REFIT UK-DALE 200 200 200 150 150 150 100 100 100 100 50 50 50 08:00 09:00 10:00 11:00 12:00 16:00 17:00 18:00 19:00 20:00 21:00 07:00 08:00 09:00 10:00 11:0 Apr 23, 2011 Apr 13, 2014 Jan 04, 2014 2000 2000 2000 1500 NICKOWAVE 1500 1500 1000 1000 500 500 23:41:00 23:41:15 23:41:30 23:41:45 23:42:00 16:27 16:28 16:29 16:30 16:31 16:32 07:49 07:50 07:51 07:52 Apr 26, 2011 May 19, 2014 Oct 10, 2013 2500 2500 2500 2000 1500 1000 500 2000 2000 1500 1500 1000 1000 500 500 01:00 02:00 03:00 04:00 05:00 15:00 16:00 17:00 18:00 19:00 08:30 09:00 09:30 10:00 10:30 11:00 May 01, 2011 May 25, 2014 Sep 07, 2013

## Latest Trends in NILM

- Eliminate the need to train a model from scratch for every house
  - Training requires extensive computation, data & time
- Edge NILM
  - NILM runs directly on the (embedded) hardware
  - Edge node learns and improves by help of local data
- Federated Learning [1]
  - Local learning with global exchange of improvements
- Pre-trained models [2]
  - Splitting learning into base models and fine-tuning
  - Viable alternative to transfer learning
  - Promising approaches: model-agnostic meta-learning and ensemble learning

[1] Zhang, Yu, Guoming Tang, Qianyi Huang, Yi Wang, Kui Wu, Keping Yu, and Xun Shao. "Fednilm: Applying federated learning to nilm applications at the edge." IEEE Transactions on Green Communications and Networking (2022).

[2] Wang, Lingxiao, Shiwen Mao, Bogdan M. Wilamowski, and Robert M. Nelms. "Pre-trained models for non-intrusive appliance load monitoring." IEEE Transactions on Green Communications and Networking 6, no. 1 (2021): 56-68.

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### Approaches for Pre-Trained Models: Model-Agnostic Meta Learning & Ensemble Learning (1)

- Inspired by BERT (ensemble learning) & GPT-3 (meta-learning)
- Model-agnostic meta-learning
  - Pre-training set serves to train the base learner (e.g., sequence-to-point model)
  - Fine-tuning is performed on a small portion of the target household
  - Important: all parameters are updated during fine-tuning (no freezing)
- Ensemble learning (stacking)
  - Training data is done on several clusters (i.e., several households)
  - Each cluster is used to train a first-level learner
  - · An additional network is used as a second learner to fuse the outcomes of all first-learners
  - Procedure for fine-tuning
    - Freeze base layers
    - Three layers of a fully-connected network are put on top
    - Train dense layers with fine-tuning data

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# (Ongoing) NILM Challenges

- Challenge 1: creating <u>reliable algorithms</u> with good generalization ability
  - How to create robust models? How to deal with noisy datasets and appliances with abnormal behavior?
- Challenge 2: developing hybrid NILM models incorporating user feedback and continuous learning techniques
  - Consumer's habits and seasonality affect energy usage patterns
  - How to use feedback to improve accuracy?
- Challenge 3: providing <u>explainable NILM models</u> with reasoning behind predictions
  - How to provide a level of trust in the consumption feedback?
- Challenge 4: providing <u>privacy-preserving outcomes</u> by help of secure NILM models
  - How to address privacy concerns in NILM applications?

Kaselimi, Maria, Eftychios Protopapadakis, Athanasios Voulodimos, Nikolaos Doulamis, and Anastasios Doulamis. "Towards Trustworthy Energy Disaggregation: A Review of Challenges, Methods, and Perspectives for Non-Intrusive Load Monitoring." *Sensors* 22, no. 15 (2022): 5872.



# Thank you.

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