UNET-NILM: A Deep Neural Network for Multi-tasks Appliances State Detection and Power Estimation in NILM

5th International Workshop on Non-Intrusive Load Monitoring
(co-located with ACM BuildSys 2020 Workshop)

NILM WORKSHOP

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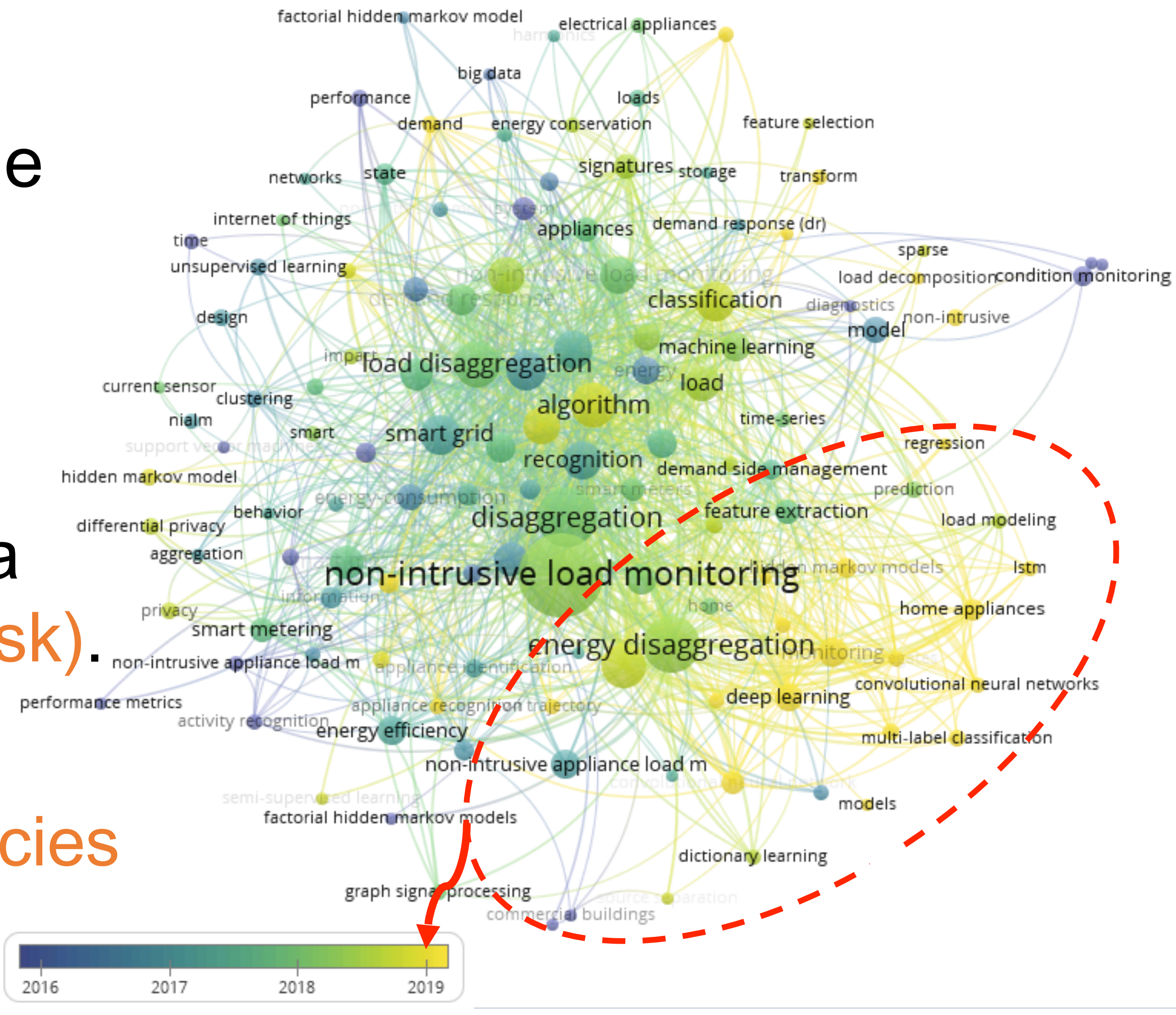
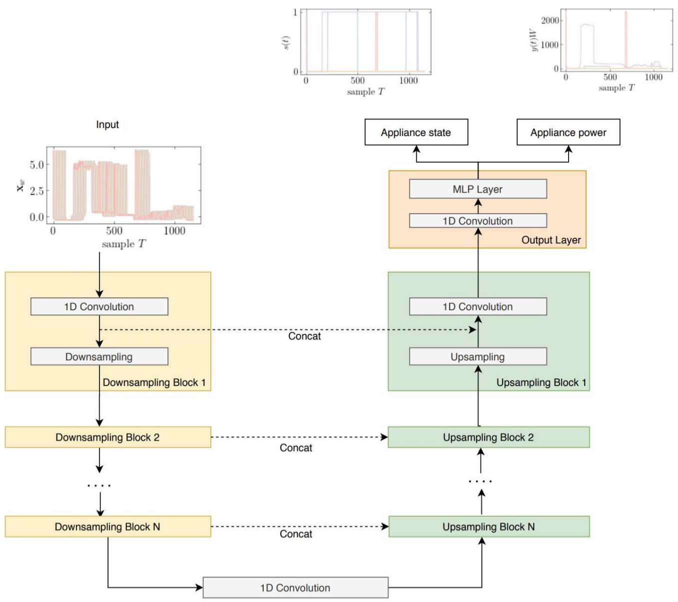
Introduction

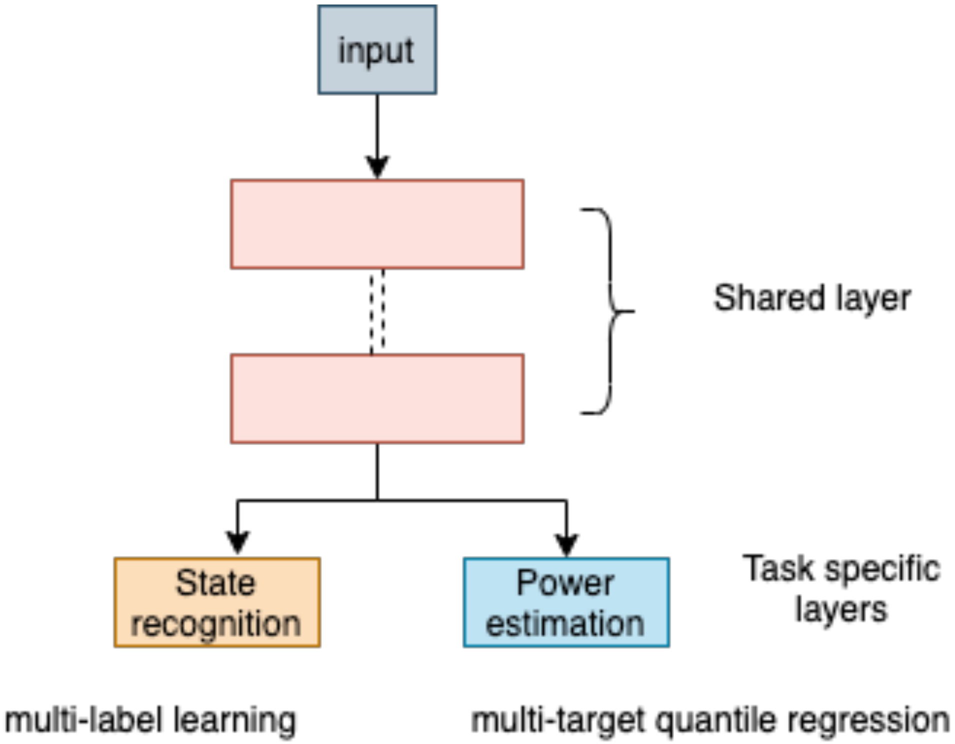
- DNNs for NILM have moved to the spotlight recently.
  - One DNN is trained for one particular appliance or task at a time (single-appliance/single-task).
  - Require a lot of computations.
  - Do not allow to learn dependencies between appliances usage



Multi-targets-multi-tasks NILM

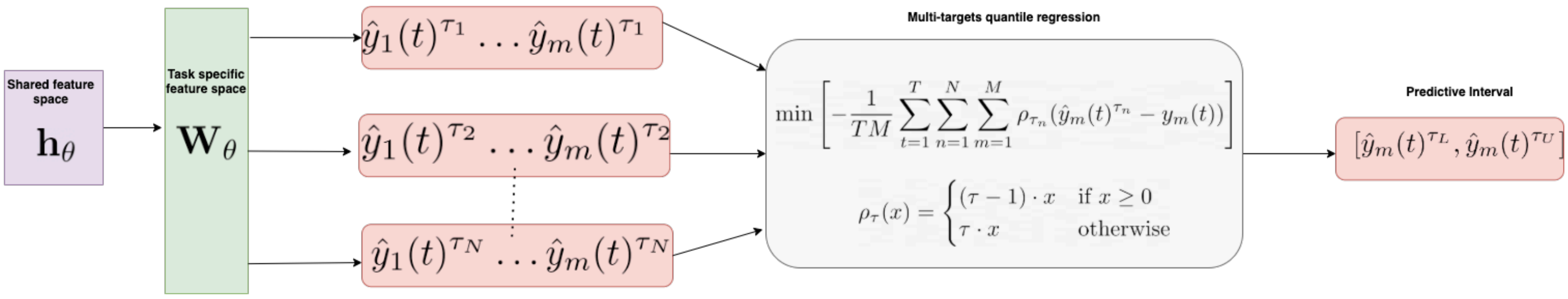
- Multi-task learning: An approach to inductive transfer that improves generalisation by using the domain information present in the training feature space of dependent tasks





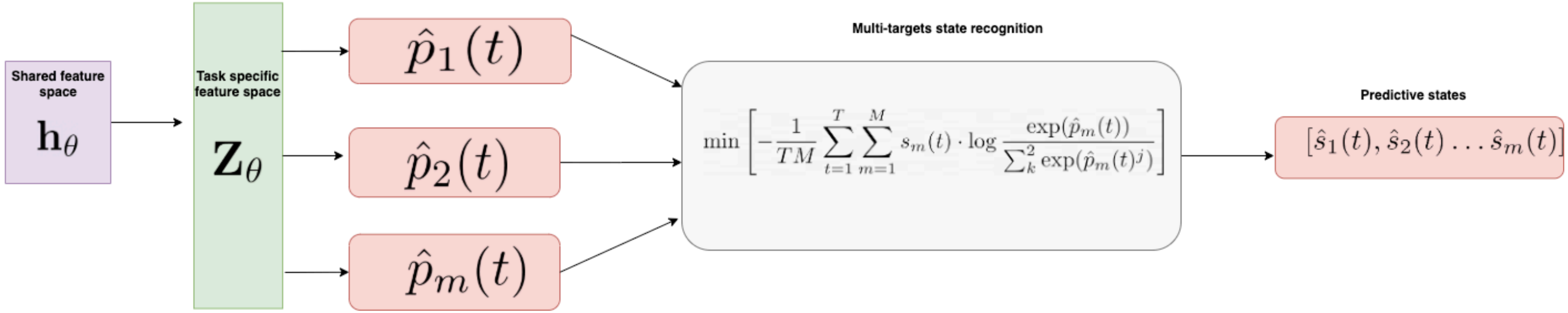
Multi-targets-multi-tasks NILM

- Multi-target Quantile Regression for Power Estimation:
  - Estimate the power of multiple appliances based on a shared feature space.



Multi-targets-multi-tasks NILM

- Multi-label learning for appliances states detection:
  - Multi-label learning aims at predicting one or more labels for each input instance



Appliance State Profile Generation

- Sequence to Quantile for state profile generation
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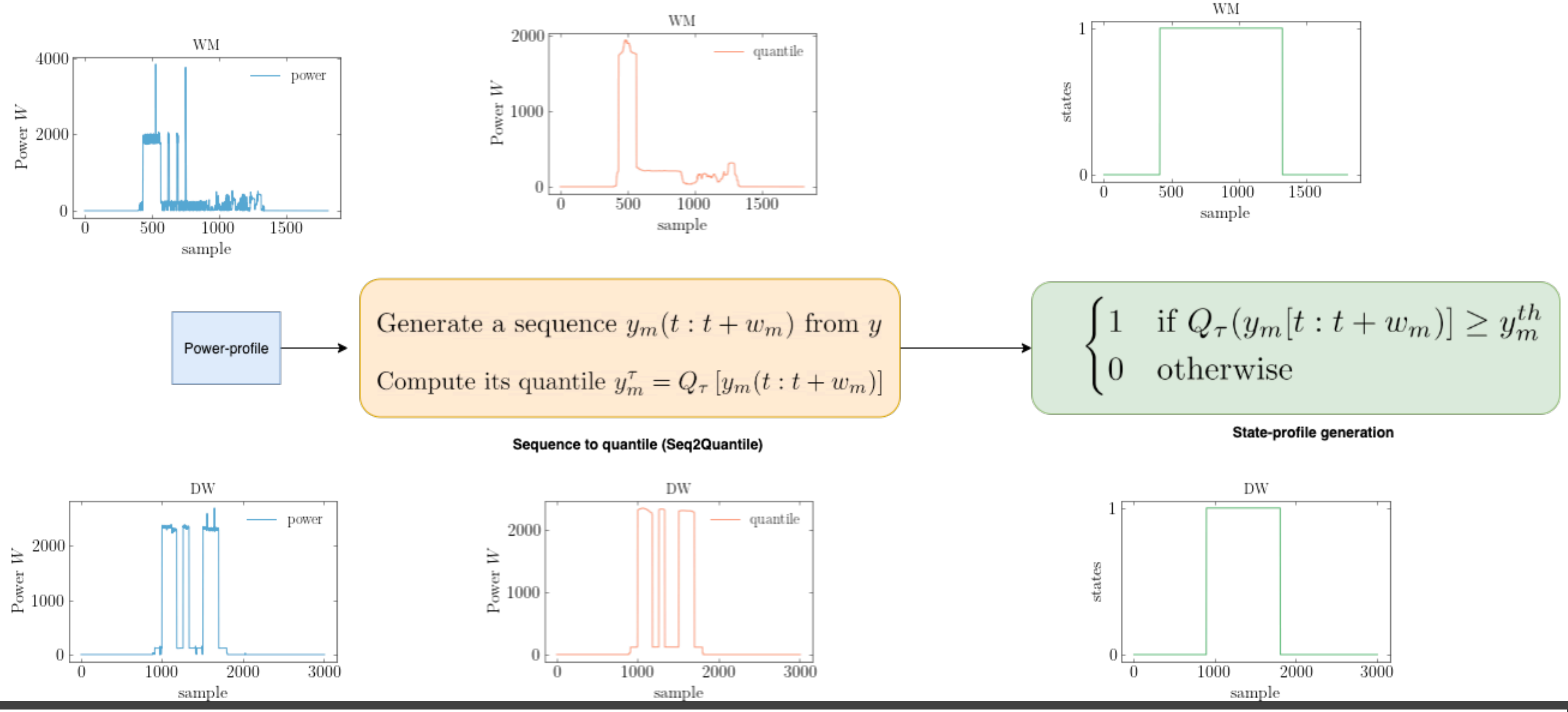
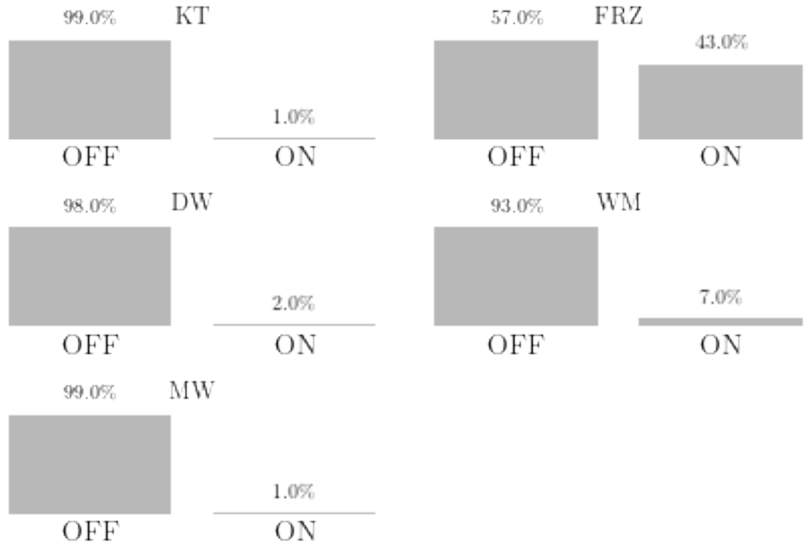


Evaluation Methodology

- Data set
  - UK-DALE house 1 (January to March)
  - with 6s sampling.

Training 60 % | Validation 20% | Test set 15%



- Kettle (KT), Fridge (FRZ), DishWasher (DW), Washing machine(WM), Microwave (MW)

Evaluation Methodology

1. Evaluation Metrics

Mean Average Error (MAE)

$$\frac{1}{TM}\sum_{i=1}^{T}\sum_{m=1}^{M}|\hat{y}_m(t) - y_m(t)|$$

MAE quantifies the error predicted power at every time point

Normalised Disaggregation Error (NDE)

$$\frac{\sum_{i=1}^{T}\sum_{m=1}^{M}(\hat{y}_m(t) - y_m(t))^2}{\sum_{i=1}^{T}\sum_{m=1}^{M}y_m(t)^2}$$

NDE measures the normalised error of the squared difference

Estimated Accuracy (EAC)

$$1 - \frac{\sum_{i=1}^{T}\sum_{m=1}^{M}|\hat{y}_m(t) - y_m(t)|}{2\sum_{m=1}^{T}\sum_{m=1}^{M}y_m(t)}$$

EAC provides the total estimated accuracy

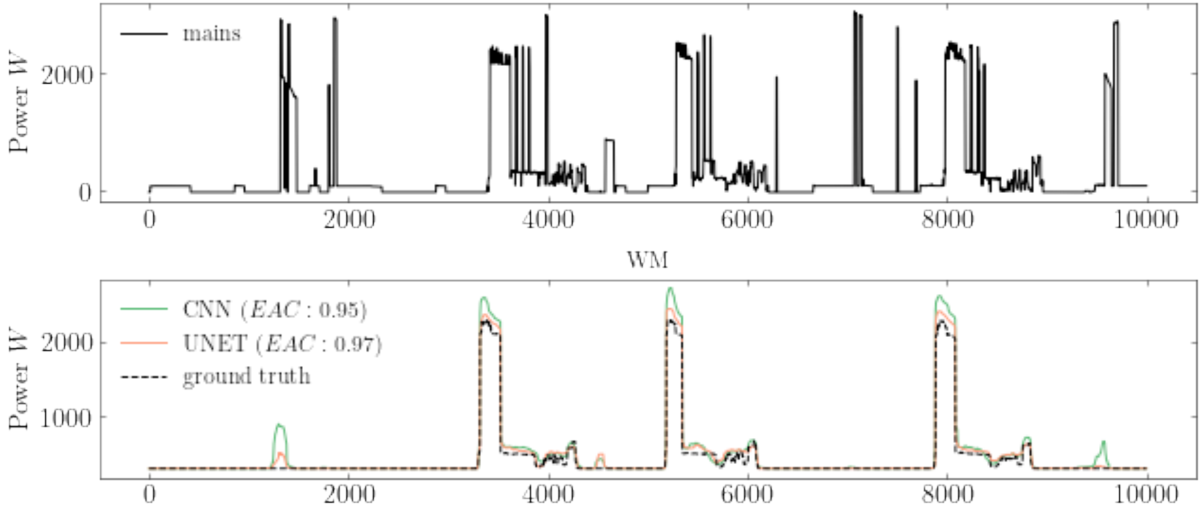
Example-based F1 (exb-f1)

$$\frac{\sum_{i=1}^{M}2\cdot t_p}{\sum_{i=1}^{M}y_i + \sum_{i=1}^{M}\hat{y}_i}$$

Exb-f1 measures the ratio of correctly predicted labels to the sum of the total true and predicted labels

Results

	EAC		MAE		NDE		$exb-F_1$	
Appliance	1D-CNN	UNet-NILM	1D-CNN	UNet-NILM	1D-CNN	UNet-NILM	1D-CNN	UNet-NILM
KT	0.589 ± 0.003	0.677 ± 0.017	20.390 ± 0.169	16.003 ± 0.824	0.674 ± 0.010	0.429 ± 0.039	0.944	0.956
FRZ	0.923 ± 0.000	0.937 ± 0.000	18.583 ± 0.006	15.124 ± 0.014	0.073 ± 0.000	0.072 ± 0.000	0.964	0.962
DW	0.875 ± 0.000	0.914 ± 0.000	9.884 ± 0.012	6.764 ± 0.012	0.126 ± 0.000	0.080 ± 0.000	0.913	0.909
WM	0.875 ± 0.000	0.909 ± 0.000	15.758 ± 0.009	11.506 ± 0.006	0.111 ± 0.000	0.062 ± 0.000	0.954	0.963
MW	0.630 ± 0.002	0.753 ± 0.003	9.690 ± 0.055	6.475 ± 0.072	0.656 ± 0.007	0.334 ± 0.005	0.907	0.916
Average	0.778 ± 0.003	0.838 ± 0.004	14.86 ± 0.050	11.174 ± 0.186	0.328 ± 0.003	0.195 ± 0.009	0.937	0.941



Conclusion & Future Work

- UNET-NILM is a multi-task NILM model that estimates both ON/OFF states and power consumption along with the uncertainty of its predictions.

- UNET-NILM demonstrated competitive results with a good confidence.

- Future Work:
  - Evaluation of the proposed approach on real aggregate with larger number of appliances and more advanced benchmarks.
  - Consider other uncertainty estimation approach.

Thank You!

For Your Attention

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