Evaluating Multi-Task Learning for Energy Disaggregation on Synthetic High-Resolution Data

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ABSTRACT

In the United States alone annual energy use has soared to over 100 quadrillion BTUs in recent years. The electrical power sector is responsible for an increasing portion of this consumption and there is a need for increased research to discover opportunities for reducing these statistics globally. Nonintrusive load monitoring, also known as energy disaggregation, has been touted as an inexpensive mechanism to obtain higher visibility into electrical demand patterns. Fundamentally, energy disaggregation is a signal unmixing problem that attempts to extract appliance-level patterns from aggregate electrical measurements. State-of-the-art approaches for disaggregation today are dominated by deep learning models. For the most part, these models cast the problem as a single task (e.g., regression, classification, clustering). To add to this body of work, we explore techniques from a sub-field of deep learning called multi-task learning for its potential in estimating electric consumption on multiple appliances at once through parameter sharing. We developed and evaluated architectures for modeling conditional source separation across multiple appliances targets simultaneously using simulated high frequency data. This solution is desirable due to its high flexibility and scalable properties as compared to traditional single network appliance-based disaggregation. Benchmarks for performance were measured using MSE, MAE, MedAE, and sequence-wise RMSE to look at effective grouping of tasks. Our preliminary results suggest that combining disaggregation tasks of appliance groups in particular configurations may outperform up to 90% (RMSE) to single-task methods. We expect our results to open the door to more multi-task studies in this field.