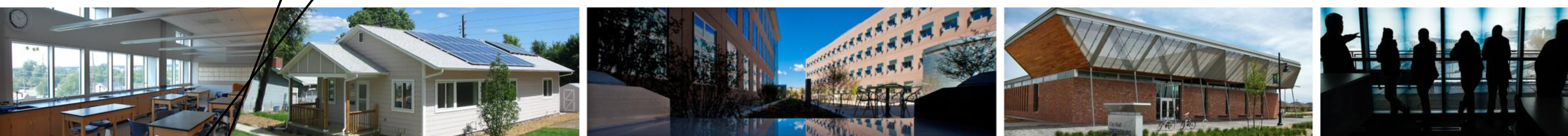
An Active Learning Framework for Non-Intrusive Load Monitoring



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National Renewable Energy Laboratory (NREL)

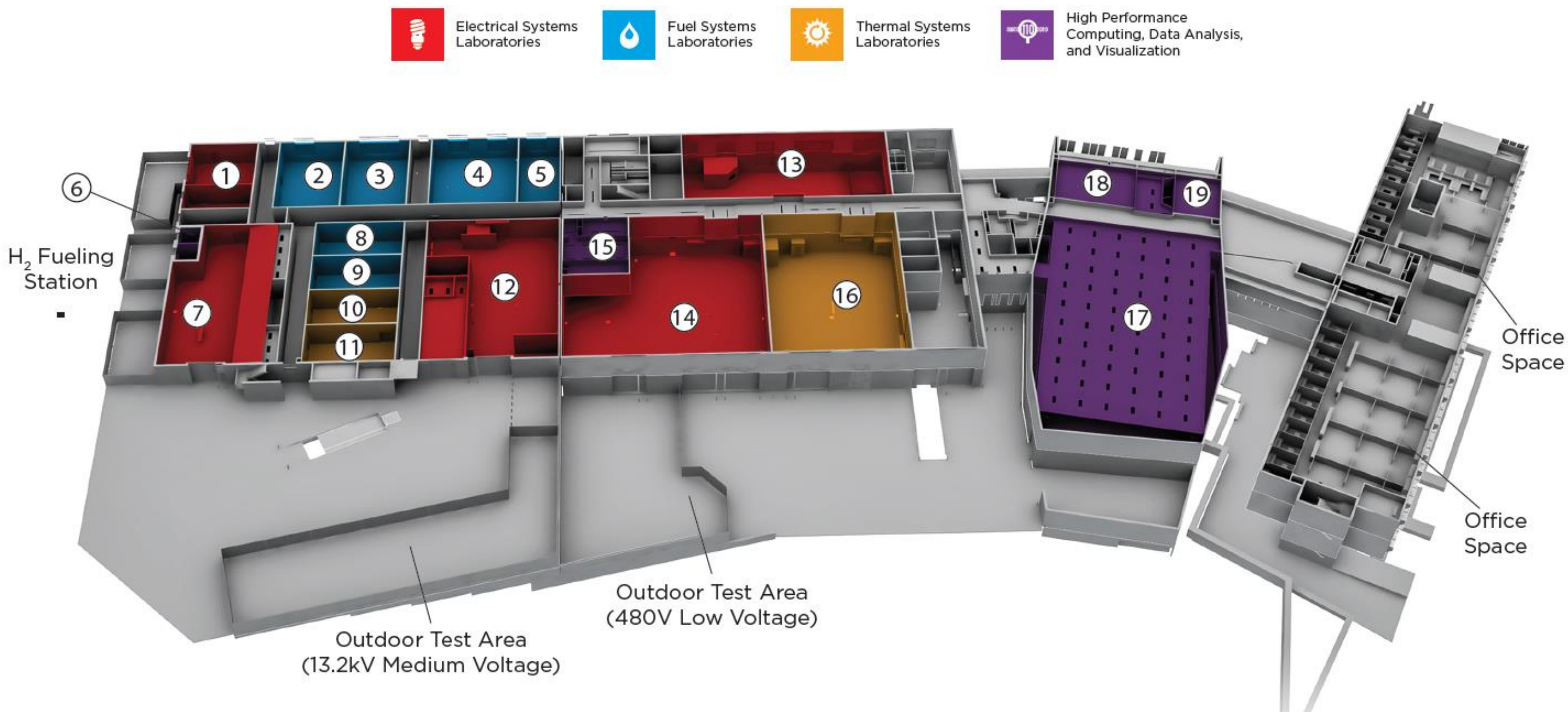
NREL is a national lab of the United States Department of Energy

- Dedicated solely to energy efficiency and renewable energy technologies
- Highest number of patents, copyrights, and technology transfers among all labs
- Focusing on advancing science and technologies to address the nation's energy and environmental goals

Image credit: Dennis Schroeder, NREL PIX#17612

Energy Systems Integration Facility at NREL

- ESIF has been named 2014 Laboratory of the Year by the R&D Magazines
- A first-of-its-kind research user facility: an ultra-energy efficient workplace, one of the most energy efficient HPC data centers, and sophisticated high-bay lab spaces
- Partners include major players in high tech, home automation, and utility industries



1. Electrical Characterization Laboratory
2. Materials Characterization Laboratory
3. Energy Systems Fabrication Laboratory
4. Fuel Cell Development and Test Laboratory
5. Manufacturing Laboratory
6. Energy Systems High Pressure Test
7. Energy Systems Integration Laboratory
8. Electrochemical Characterization
9. Energy Systems Sensor Laboratory
10. Thermal Storage Materials Laboratory
11. Thermal Systems Process and Component
12. Energy Storage Laboratory
13. Smart Power Laboratory
14. Power Systems Integration Laboratory
15. Control Room
16. Optical Characterization Laboratory
17. High Performance Computing Data Center
18. Insight Center Collaboration Room
19. Insight Center Visualization Room

Work with NREL

Why work with NREL?

- World-class testing facilities and researchers
- Strong partnership with clean technology industry
- Recognized neutral third-party for technology validation

NREL is the Technical Lead for DOE's Building America program

- Develop cost-effective efficiency solutions for residential buildings
- Demonstrated in over 45,000 homes over past 20 years across the U.S.
- Partnership with industry (including many of the top U.S. home builders) to bring cutting-edge innovations and resources to the market

Ways to work with NREL

- ESIF User Facility Program
- Strategic partnership
- Cooperative Research and Development Agreement (CRADA)
- Wells Fargo Innovation Incubator Program (for clean tech startups)
- Funding opportunity collaboration (DOE, non-DOE, SBIR/STTR, etc.)

Key Barriers to Wide Adoption of NILM

NILM technology has existed for more than two decades but still hasn't been widely adopted in most homes. Key barriers include:

- **Non-trivial initial setup is required**
  - Need to provide excessive information to train the NILM algorithms
  - Need to install additional hardware, such as current sensors to the service mains – which should only be done by a qualified electrician
- **Performance of NILM systems can be improved**
  - Pattern libraries cannot be shared among different suites of appliances
  - Difficult to achieve high disaggregation accuracy with limited user inputs
- **Cost of NILM systems are still higher than desirable**
  - The additional hardware (current/voltage sensors, displays, etc.) keeps NILM systems expensive
  - Software-based NILM systems are less expensive but they offer less granular disaggregation results

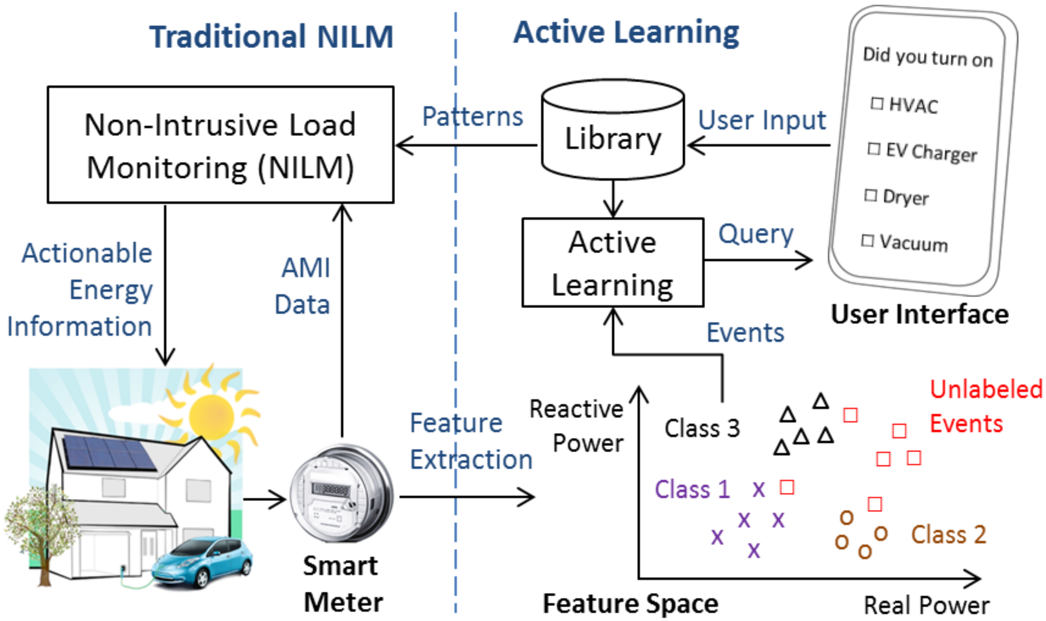
A Modular Approach to NILM

- Hundreds of NILM methods have been developed but most of those methods work on their own and do not interoperate
- Every NILM method has its own strength in solving subproblems of NILM:
    - Appliance signature extraction
    - Event detection and/or classification
    - Interaction with users
    - …
- **Can we make NILM methods modular** to help build up more robust systems using separate state-of-the-art approaches for each subproblems?

Active Learning-based NILM

What is active learning?

- A machine learning method that interactively queries the user for the class label information
- Widely adopted in scenarios where labeled samples are difficult, time-consuming or expensive to obtain
- A perfect fit for the NILM problems where data are abundant but labels are expensive to obtain



An active learning framework for augmenting existing NILM systems

Why does AL work for NILM?

- Not all samples need to be labeled by the user; some samples are more informative
- We can use as few labeled samples as possible while still achieving high accuracy
- AL overcomes the key barriers of NILM by minimizing the cost of obtaining class labels

Pool-based Active Learning with L^2 Norm

Pool-Based Sampling:

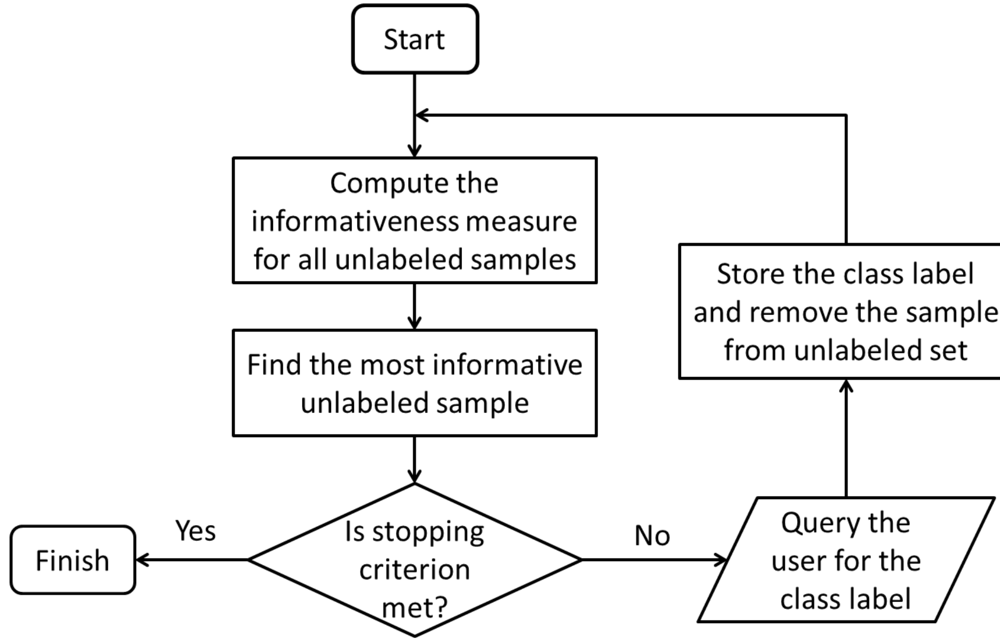
Large collections of unlabeled samples can be collected at once and queries are selectively drawn from the pool

Problem Formulation:

Active learning aims to find an unlabeled sample $\boldsymbol{x}_q$ such that

$$\boldsymbol{x}_q = \underset{\boldsymbol{x} \in \boldsymbol{X}_U}{\operatorname{argmax}} \frac{1}{n} \sum_{i=1}^{n} d(\boldsymbol{x}, \boldsymbol{x}_i)$$

where $\boldsymbol{x}_i \in \boldsymbol{X}_K$, $\boldsymbol{X}_K$ is a set of labeled samples, $\boldsymbol{X}_U$ is a pool of unlabeled samples, $d(\boldsymbol{a}, \boldsymbol{b})$ is the **L**^{2} Norm, and $\frac{1}{n}\sum_{i=1}^{n} d(\boldsymbol{x}, \boldsymbol{x}_i)$ is the *informativeness measure*.



Procedures for generating a query:

- Compute the informative measure
- Identify the most informative sample
- Check the stopping criterion
- Obtain the class label from the user
- Store the label and remove the sample

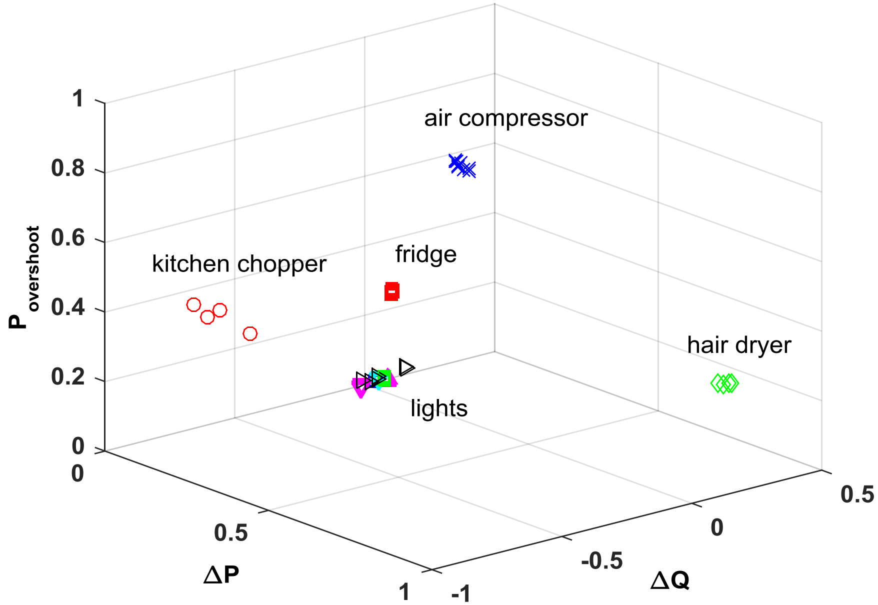
Experiments on BLUED Dataset

BLUED Dataset

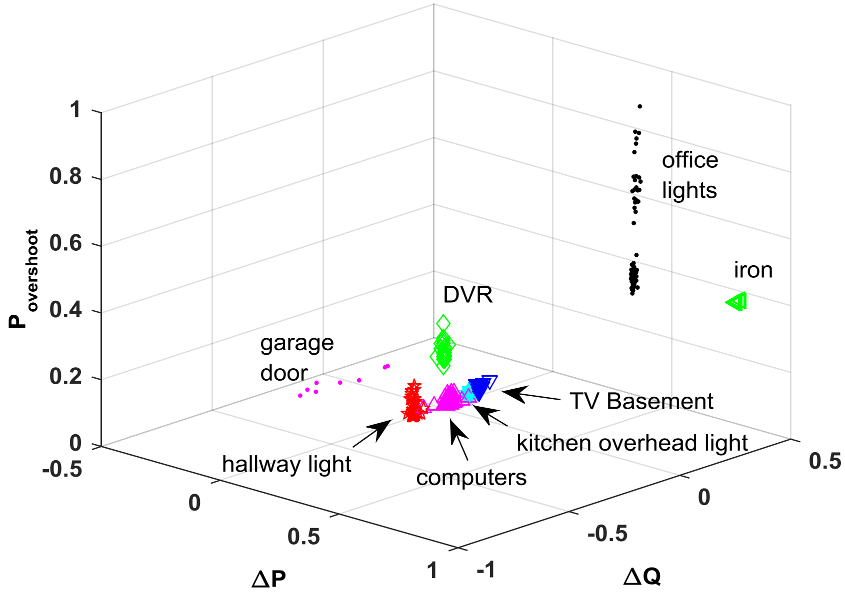
- BLUED is a fully labeled public dataset for event-based NILM research
- Voltage and current measurements were sampled at 12 kHz for a whole week
- Every state transition of each appliance was labeled and time-stamped

Feature Extraction

- The raw voltage and current data were converted to 60 Hz power data
- 150 data points were taken around an event, simulating an ideal event detector
- ΔP, ΔQ and $P_{overshoot}$ (transient real power overshoot) were extracted as features



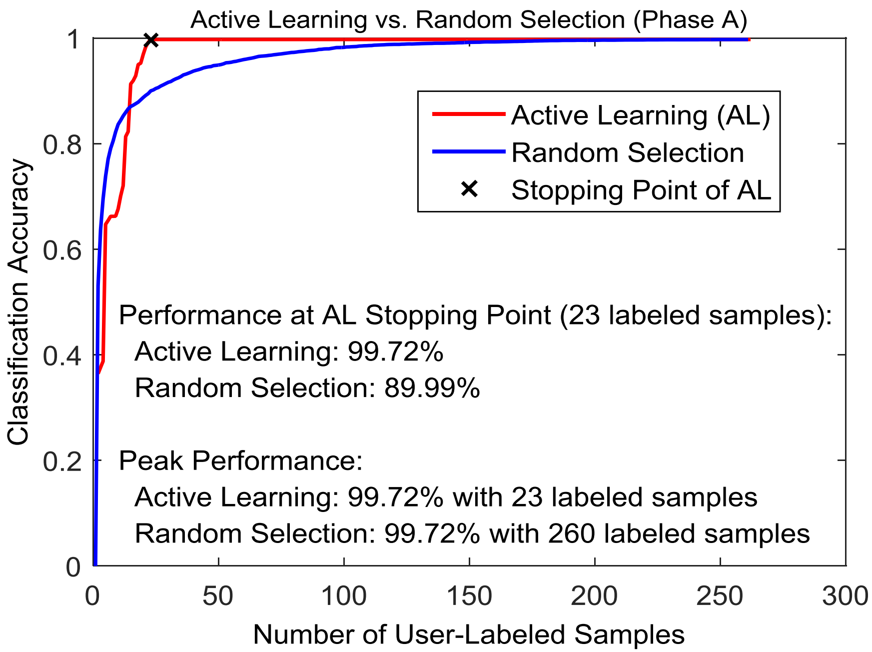
Examples of Phase A events in the feature space

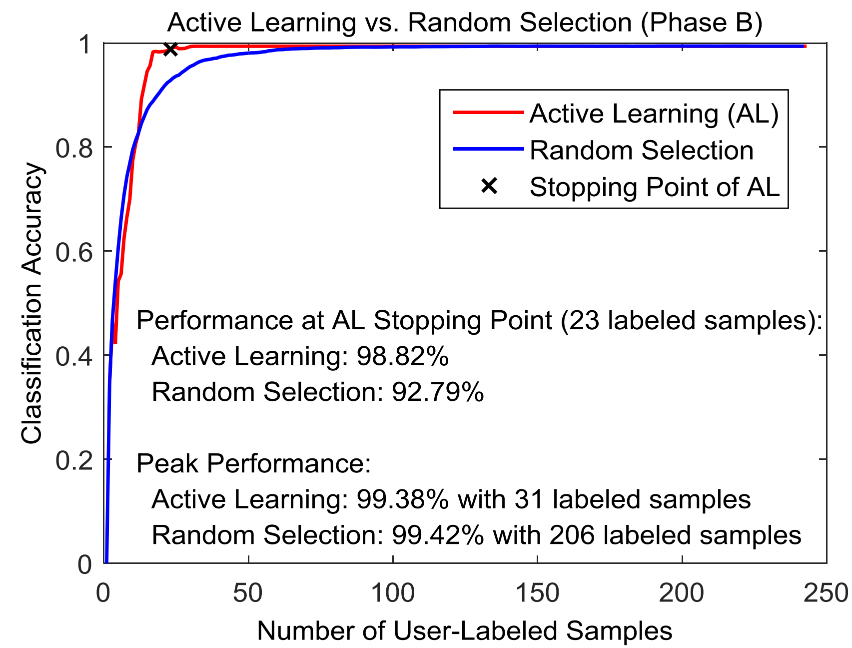


Examples of Phase B events in the feature space

Results

- A four-fold cross validation is implemented
- A *k*-NN classifier is included in the learning loop to perform event classification every time a new label is provided by the user
- A random selection algorithm is implemented for comparative evaluation
- Both algorithms are implemented for 50 iterations





The active learning method reaches its peak (or near peak) performance by automatically selecting only using 10% of the total user-labeled samples

Conclusion

- The proposed active learning method provides **a modular solution** for augmenting existing NILM systems
- The proposed method only needs the **minimally sufficient information** to build a compact yet highly representative load signature library by **querying the most informative samples first**
- The proposed method is able to **reduce the user inputs by up to 90%** while still achieving **similar disaggregation performance** compared to a heuristic method
- The proposed method has the potential to **overcome the key barriers** to the wide adoption of NILM technologies
  - **User Inputs**: substantially reducing the burden on the user
  - **Performance**: improving the performance of a NILM system with very limited user inputs
  - **Cost**: minimizing the incremental cost over existing systems by implementation in the cloud or on mobile platforms

Future Research

- Extend active learning to **proactive learning** that does not assume the user is *infallible* or *indefatigable* to bridge the gaps
- Combine active learning with **semi-supervised learning** to further reduce the labeling effort
    - Active learning: exploit the least confident samples
    - Semi-supervised learning: exploit the most confident samples
    - Combined learning scheme: only highly uncertain samples are labeled by a user and all others are automatically labeled
- Explore other **informativeness measures** other than the Euclidean distance, such as information-theoretic measures
- Develop a **labeling assist** module that uses time/frequency-of-use to infer the appliance information to reduce the labeling effort
- **Integrate** active learning-based NILM techniques to address all of the energy sensing needs in a home: electricity, water & gas




Thank You!