Appliance Level Energy Disaggregation
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Motivation
- The way we think about energy is in need of reform!
- Even with the rise of smart meters, we have very limited information of the way we consume energy
- In Roble alone, utility bills have exceeded over $4 million over the past 10 years
- Every winter, Roble saves 1000 metric tons CO2
- How can we conserve our energy and save money?

Data / Problem Formulation

REDD Dataset
- 6 Homes (plugwise data from ~10 appliances)
- Sampling Frequency
  - low_freq, high_freq
- Location: Boston, MA
- Duration: 12 months

TRAINING STRUCTURE

Generate Lag Intervals

KNN Regression SVM Sparse Coding RF

Time Step Dish Washer Fridge Light Socket Dryer
1 43.68 82 21 4.1 2.3
... ... ... ... ... ...
31566 ... ... ... ... ...
31567 46.8 72.3 29.7 10.6 0.7

Approach
- Train a separate models for each class of appliance into a dictionary. Use these models to separate aggregate signal.

$$X_i \approx B_i A_i, \quad B_i \in \mathbb{R}^{T \times k}, A_i \in \mathbb{R}^{k \times B}$$

$$\text{Loss} = \min_{A_i, B_i, B_{i+1}} \left[ \frac{1}{2} ||X_i - B_i A_i||^2_F + \lambda \sum_{i=1}^{T} ||A_i||_2^2 \right]$$

Accuracy = \frac{\min \{ \sum_i \sum_j (X_{ij} - \hat{X}_{ij})^2 \}}{\sum_i X_{ij}}

Future Work
- Gather larger dataset representative of true population
- Utilize user metadata as predictive features
- Experiment with RNN to capture temporal dependence
- Experiment with ensembling

Analysis and Evaluation

Model Performance
- We monitor model loss for sparse coding, the frobenius norm between the sparse reconstruction of the electricity usage time series

Dictionary Loss

Activation Loss

Train / Test Accuracy

<table>
<thead>
<tr>
<th>Model</th>
<th>Train Acc</th>
<th>Test Acc</th>
</tr>
</thead>
<tbody>
<tr>
<td>KNN</td>
<td>56.94%</td>
<td>45.68%</td>
</tr>
<tr>
<td>Regression</td>
<td>73.72%</td>
<td>68.54%</td>
</tr>
<tr>
<td>SVM</td>
<td>82.18%</td>
<td>78.22%</td>
</tr>
<tr>
<td>Sparse Coding</td>
<td>92.89%</td>
<td>90.14%</td>
</tr>
</tbody>
</table>

Learned Appliance Signatures
- Sparse coding network predicts each appliances’ time series. Through our base lines, we see that linear models perform poorly.
- Seeking to capture nonlinear relationships, we find that SVMs, Neural Networks and Sparse Coding are able to better identify each appliances’ signature.
- We also find that adding more meaningful features (boston weather data) helps build a more powerful predictive network.

Conclusions
- Successfully implemented a variety of predictive networks for disaggregating home energy data
- Model can decipher appliance identity conditioned on aggregate energy over previous time steps
- Nonlinear models are able to capture more sophisticated dependencies, as hypothesized.
- Generalizability remains a challenge