Appliance Level Energy Disaggregation

Samir Sen, Fred Lu | {samirsen, fredlu}@stanford.edu

Motivation

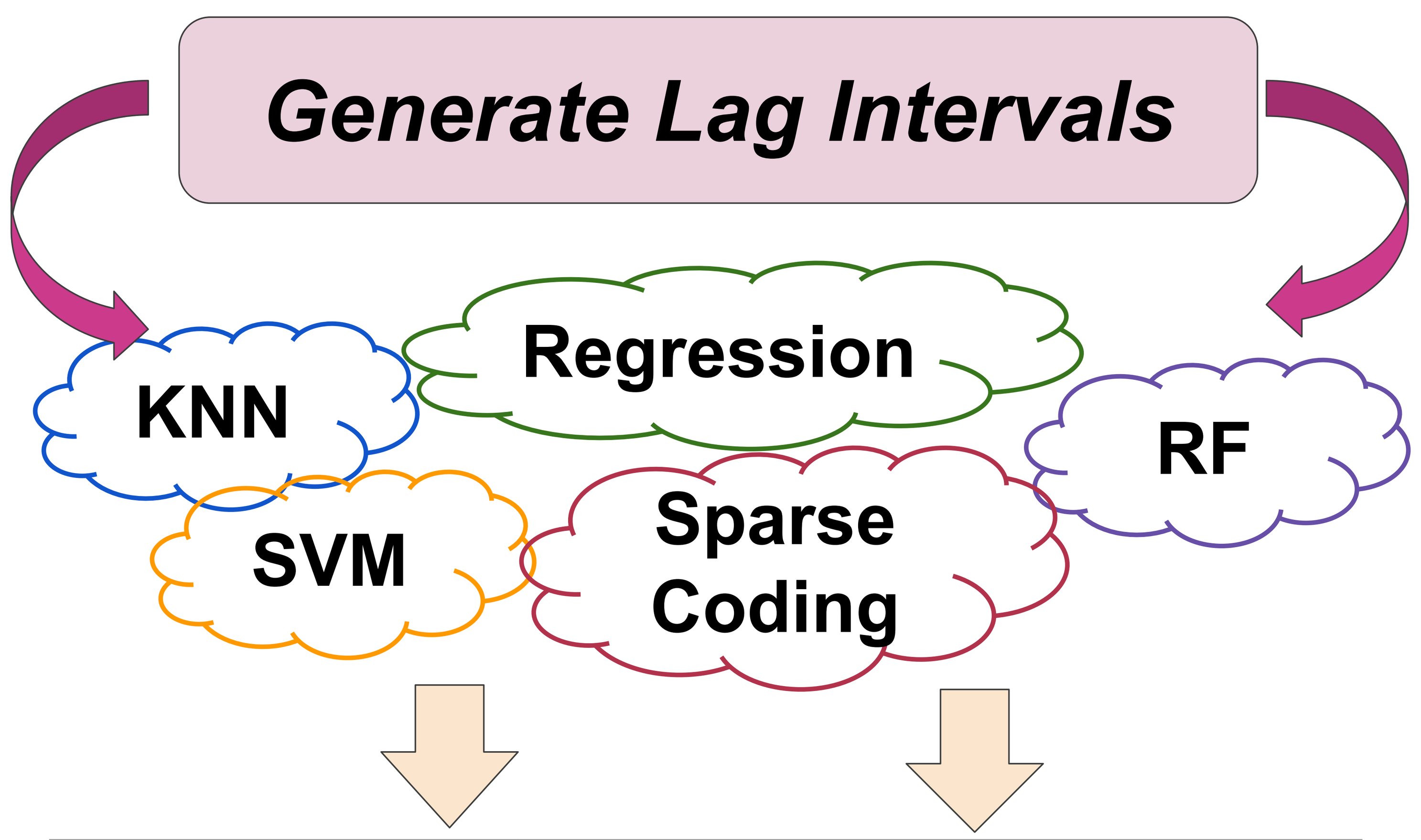
- The way we think about energy is in need of reform!
- Even with the rise of smart meters, we have very limited information of the way we consume energy
- In Roble alone, utility bills have exceeded over $4 million over the past 10 years
- Every winter, Roble saves 1000 metric tons CO2
- How can we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



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

Experiments

Base Modeling

True | **Predicted** | **Inference**

KNN

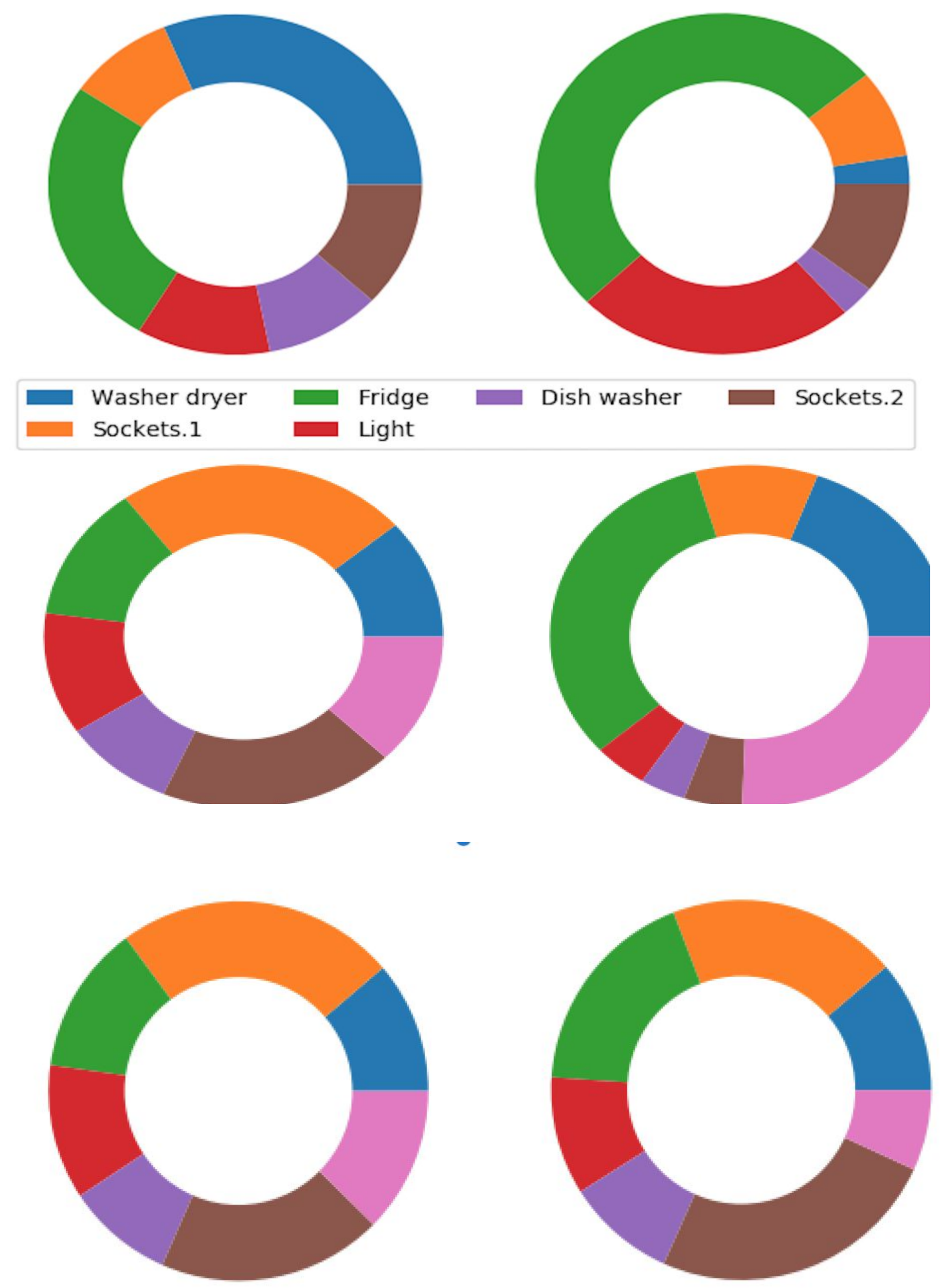
$$y_i = \frac{1}{k}\sum_{j=1}^{k} X_{j,i}$$

Regression

$$y_{i,t} = \beta_0 + \sum_{j=1}^{100}\beta_j \cdot x_{i,t-j}$$

SVM

$$y_{i,t} = \beta_0 + \sum_{j=1}^{100}\beta_j \cdot \phi(x_{i,t-j})$$



Sparse Coding Network

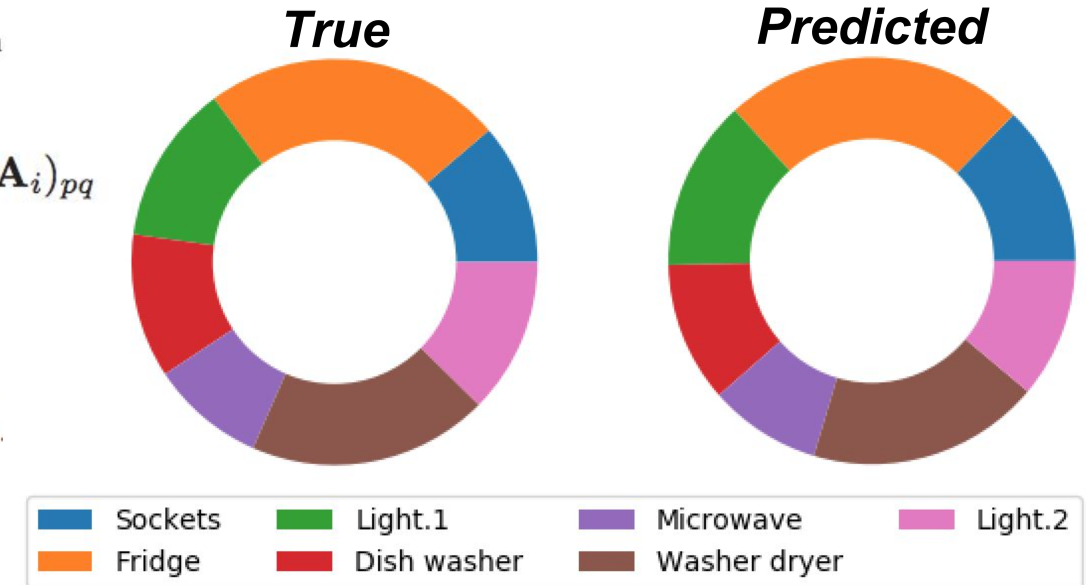
Approach

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

$$\mathbf{X}_i \approx \mathbf{B}_i\mathbf{A}_i \quad \mathbf{B}_i \in \mathcal{R}^{T\times n}, \mathbf{A}_i \in \mathcal{R}^{n\times m}$$

$$\text{Loss} = \min_{\mathbf{A}_i \geq 0, \mathbf{B}_i \geq 0} \frac{1}{2}\|\mathbf{X}_i - \mathbf{B}_i\mathbf{A}_i\|_F^2 + \lambda\sum_{p,q}(\mathbf{A}_i)_{pq}$$

$$\text{Accuracy} \equiv \frac{\sum_{i,q}\min\left\{\sum_p(\mathbf{X}_i)_{pq}, \sum_p(\mathbf{B}_i\hat{\mathbf{A}}_i)_{pq}\right\}}{\sum_{p,q}\bar{\mathbf{X}}_{p,q}}$$



Future Work

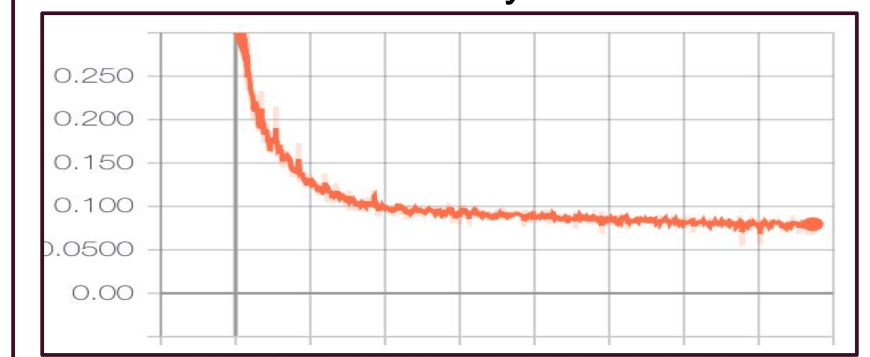
- Gather larger dataset representative of true population
- Utilize user metadata as predictive features
- Experiment with RNN to capture temporal dependence
- Experiment with ensembling

Analysis and Evaluation

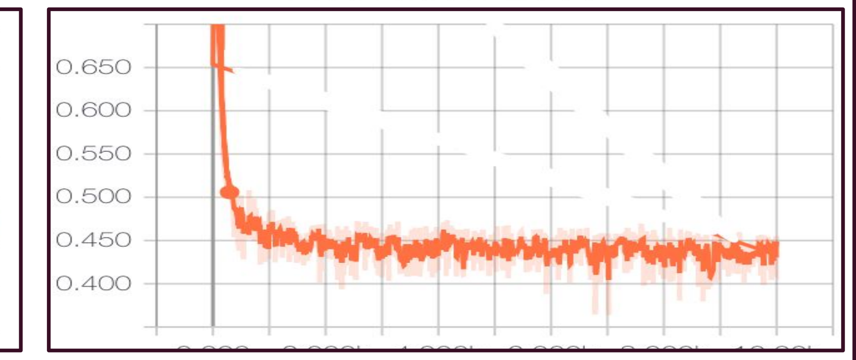
Model Performance

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

Dictionary Loss



Activation Loss

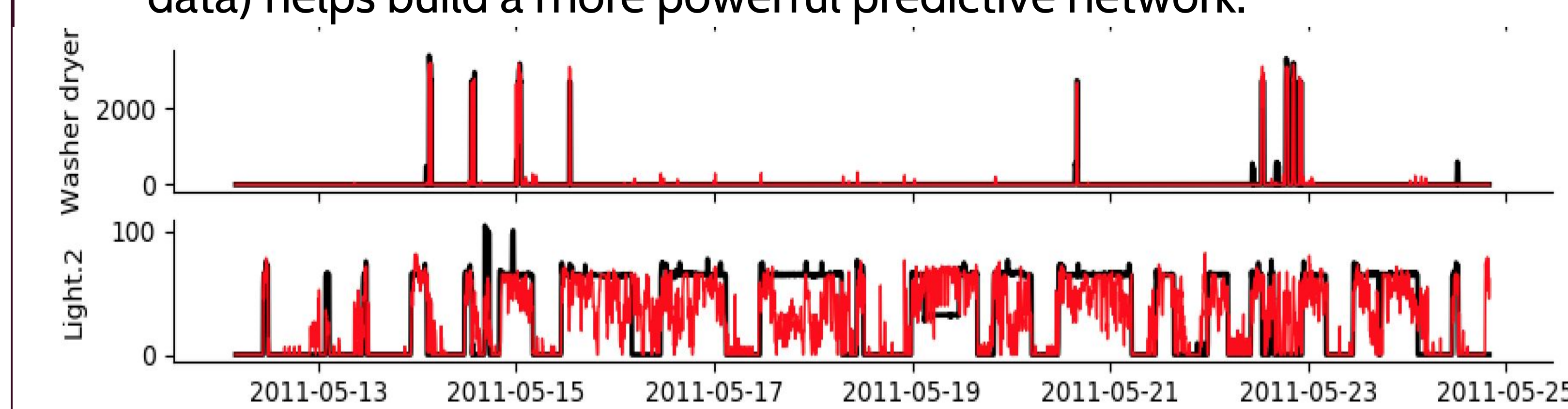


Train / Test Accuracy

Model	Train Acc	Test Acc
KNN	56.94%	45.68%
Regression	73.72%	68.54%
SVM	82.18%	78.22%
Sparse Coding	92.89%	90.14%

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