Modeling Electrical Loads With VAE Variants

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Summary

In our work, we model how an increase in the adoption of electric vehicles (EVs) will impact electric load curves. We focus on a per household, per day sample basis and learn:

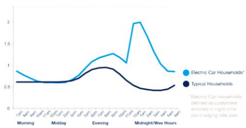
- **Latent space distributions over general load and EV load**.
- **Manipulatable conditional variable** in latent space, that makes it possible to add or remove EV load to a particular sample.

We train conditional VAE models with (a) feed-forward and (b) LSTM encoders and decoders as a method to generate electric load profiles for households with and without electric vehicles using generative models.

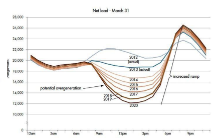
- We **share the model parameters** for the two VAEs in order to leverage the larger dataset of general load samples.

Our approach of applying generative models to electric load time series data is a **novel application area**; the prior literature relevant to our implementation applies generative models to other kinds of time series.

Background



Net load of houses w/o EV (kW)



Impact of solar and EV on grid

- Load curves are traditionally modelled with few fixed templates.
- But every household has a unique load profile, and households with EVs have different preferences when to charge their vehicles.
- Being able to learn a true distribution over the different household characteristics makes it possible to model realistic future scenarios.
- The recent rise of distributed solar energy and electric vehicles puts **stress on the electric grid** and makes it important to model loads better.

Dataset

We leverage a subset of the Pecan street dataset, containing electricity measurements for 60 different households from 2015-2018 in the form of electric load time series data, with **separate EV load measurements**.

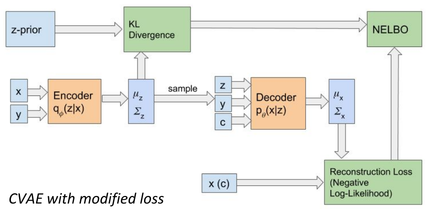
- 223,270 days, of which 21,913 have EV load > 0.1kWh
- Electric load measurements over 15 or 60 minute intervals
- 80% train, 10% validate, 10% test split

Validation and test metrics are computed over days with EV load only.

Technical Methods

Conditional VAE Model

- Minimize negative ELBO loss
- **Conditional y** {0, 1} for x {no-EV, EV}, given by data
- **Manipulatable conditional c** {-m, +m} for x(c) {remove EV, add EV}, where m = m*10kWh
- Variance penalty β in reconstruction loss, for more detailed samples. For β = 1, negative Log-Likelihood of the data under $\mu_\varphi(z)$, $\sigma_\varphi^2(z)$



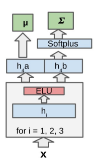
CVAE with modified loss

$$ELBO(x;\theta,\phi) = E_{q_\phi(z|x)}[\log p_\theta(x|z)] - D_{KL}(q_\phi(z|x)||p(z))$$

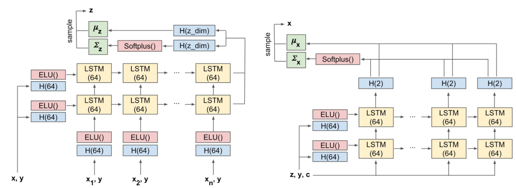
$$-\log(p(x|z)) = -\log(Normal(x|\mu_\phi(z), \sigma^2(z))) = \frac{1}{2}\left[\frac{(y-\mu_\phi(z))^2}{\sigma^2} + \beta\log(\sigma^2) + \log(2\pi)\right]$$

Encoder and Decoder Models

We compare a feed-forward NN (FF-NN) with 3 hidden layers and and a LSTM with 2 layers.



FF-NN Enc/Dec



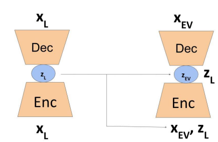
LSTM Encoder and Decoder Architecture

Training Setup

- Retrieve **two batches**: from dataset with EV load (x_0& x_1) and without EV load (x_{none})
- Run CVAE to **identity map** both batches. x_0-> x_0, x_1-> x_1 and x_{none}-> x_{none}
- Run CVAE for EV batch to **conditionally add/remove EV** load. x_0-> x_1 and x_1-> x_0

Future Work

We will extend our model using a **dual CVAE architecture**. One VAE will be trained to model general load curves, and the second will be trained to model isolated EV load curves, relaxing the parameter sharing constraint. We will also work to improve performance of our LSTM model on the noisier 15-minute resolution data and incorporate some **metadata** like day of week and weather variables.



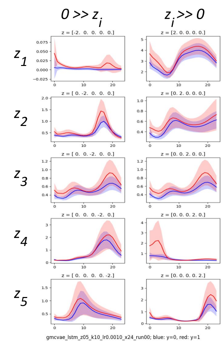
Experiments

We ran experiments to determine the following hyperparameters

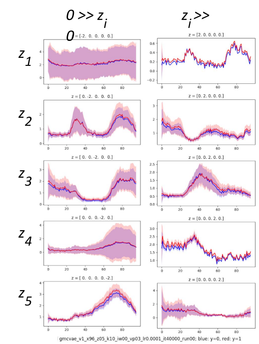
- Resolution of data : 24 vs 96 samples per day
- Model Architecture: Feed-forward vs LSTM
- Gaussian Mixture VAE, Importance Weighted VAE
- Further, we found optimal values for learning rate (0.0003), z-dimensions (5), penalty for large variance estimate(5x), fixed variance during warmup (False), log-transformed data (False)

Results - Latent Representations

The VAEs learn reasonably **disentangled latent representations** that model: base load, peak time, curve shape, daytime/nighttime activity, confidence in estimate



GM-VAE LSTM (24)



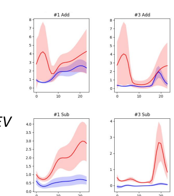
GM-VAE FF-NN (96)

Results - Conditional Manipulation

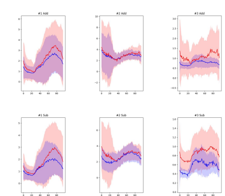
The LSTM learns a reasonable EV load shape, but is inflexible and subtracts to zero. The FF-NN is more flexible, adding/subtracting fto/from the main peak, but does not learn reasonable EV load shapes. More work is needed here.

Add EV (40 kWh)

Subtract EV (40 kWh)



GM-VAE LSTM (24)



GM-VAE Feed-Forward (96)