A Machine Learning Approach to Demand Response Supply Estimation

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Energy System Transition

- The 3Ds
  - decarbonization
  - decentralization
  - digitalization

- Demand response among end-users
  - engage
  - activate
  - harness

- Contract design for demand response
  - consumption patterns
  - population heterogeneity
Outline

1. Background
2. Data (Verification)
3. Model
4. Results
5. Conclusion
Demand Response

- Load shifting/shedding
  - minimize impact on comfort
  - focus on (ultra) short-run
    - 5–15–30 minutes
    - repeated engagement

- Applications
  - managing local grid capacity constraints
  - bid demand flexibility into electricity markets
  - price spikes/black outs
Research Project

- Sloan Foundation Project: Bilateral Contract Design and Retail Market Development for Flexible Electric Power Systems with Residential Demand-side Participation
- WSU housed project
- WSU’s Energy System Innovation Center and Smart City Testbed.
  - integrated Energy/Distribution Management System
  - integrated with a complete city feeder model
- WSU’s Center for Institutional Research Computing (CIRC).
  - Kamiak condominium HPC
  - 3800+ CPU cores in 70+ computational nodes
Nonintrusive Usage Detection

- Utilize smart meter data
- Aggregate consumption in 5 minutes intervals
- Access to meter readings for some 16 000+ customers
- Model individual consumption patterns
- Want to detect HVAC/hot water heater usage
Project Outline

- Detect consumption patterns
- Estimate marginal WTP for load
- Map population/customer heterogeneity
- Construct demand response supply function
- Design contracts for demand response programs
- Assess impact on local grid conditions (WSU Smart City Testbed)
- Bundling for market interaction?
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Pecan Street Data
Pecan Street Data

- Pecan Street data:
  - publicly available data
  - 25 houses in Austin, TX

- Behind the meter readings
  - intrusive experimental setup
  - detailed information
  - 1-minute resolution

- Known usage

- Using for verification
Load and Temperature

- Temperature
- Total load
- Air condition
- Electric car

Time: 05:14 00 to 05:16 00
Load and HVAC

The graph shows the load and air condition over time. The y-axis represents the load in kW, ranging from 0 to 3.5. The x-axis represents the time, from 05-15 00 to 05-16 00. The graph includes two lines: one for total load and another for air condition. The total load line is represented by black color, while the air condition line is represented by blue color.
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Machine Learning

- Model individual household consumption patterns
- Large volumes of data
- Machine learning
  - statistics/mathematics
  - computer algorithms
- Econometrics
  - structural models
- Oxymoron: structural machine learning
Switching Regression

- Consumption data from meter readings, high time resolution
- Consumption depends on unobserved household activities
- Model activities as hidden states
- Activities change over time
  - transitions from state to state
- Model as time-varying hidden Markov model
  - Hamilton (1989) regime-switching article
  - Bengio and Frasconi (1996) input-output HMM
- Consumption is a switching (Tobit) regression model
Hidden Markov Model

\[
\begin{align*}
\cdots & \quad S_t & \quad S_{t+1} & \quad \cdots \\
& \quad \Pr(S_{t+1}|S_t) & \\
& \quad \Pr(y_t|S_t) & \quad \Pr(y_{t+1}|S_{t+1}) \\
\cdots & \quad y_t & \quad y_{t+1} & \quad \cdots
\end{align*}
\]
Output Hidden Markov Model (switching regression model)

\[ S_t \quad \xrightarrow{\text{Pr}(S_{t+1}|S_t)} \quad S_{t+1} \]

\[ \xrightarrow{\text{Pr}(y_t|S_t, x_t)} \quad y_t \quad \xrightarrow{\text{Pr}(y_{t+1}|S_{t+1}, x_{t+1})} \quad y_{t+1} \]

\[ \xrightarrow{\text{Pr}(X_t)} \quad X_t \quad \xrightarrow{\text{Pr}(X_{t+1})} \quad X_{t+1} \]
Input-Output Hidden Markov Model

The diagram illustrates a Hidden Markov Model (HMM) with the following components:

- **States (S)**: $s_t$, $s_{t+1}$, $z_t$, $z_{t+1}$
- **Observations (y)**: $y_t$, $y_{t+1}$
- **Inputs (x)**: $x_t$, $x_{t+1}$

Where:

- $\Pr(y_t | s_t, x_t)$
- $\Pr(y_{t+1} | s_{t+1}, x_{t+1})$
- $\Pr(s_{t+1} | s_t, z_t)$

The model transitions from state $s_t$ to $s_{t+1}$ with probabilities $\Pr(s_{t+1} | s_t, z_t)$, and from state $s_t$ to $y_t$ with probabilities $\Pr(y_t | s_t, x_t)$.
Model Estimation

- Input-output Hidden Markov Model
- Observed consumption: Tobit model
- State transition probabilities: multinominal logit
- Joint estimation of all parameters
  - EM algorithm (Baum-Welch)
  - Custom code in Python
  - Using WSU Kamiak HPC cluster system
Transition Probabilities
EM Estimator

E step

HMM

M step

Transition probabilities
- state 1 (MNL)
- state 2 (MNL)
- ....
- state n (MNL)

Consumption Function
- state 1 (Tobit)
- state 2 (Tobit)
- ....
- state n (Tobit)
Python Code

- Object based
- Vectorized
- Modular
  - RegModel
    - Tobit
    - multinominal logit
  - HiddenMarkovModels
    - static transition matrix
    - variable transition matrix
  - TobitIOModel
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Predicted Consumption

- Pecan Street data: 24 houses
- Focus on summer months (200 000 obs)
- Typically 6–8 states sufficient
- Get predicted consumption $\hat{y}_t^s$
- Get predicted probabilities $\hat{\pi}_t^s$
- Averaged prediction
  \[ \hat{y}_t = \sum_s \hat{\pi}_t^s \hat{y}_t^s \]
- Substantial improvement in prediction
Load Prediction

[Graph showing load prediction over time]

- Total load
- Predicted load

Bergland and Love (WSU)  Demand Response Estimation
State Predictions

- AC states are clearly identifiable (for 22 houses)
  - 3–5 “AC” states
  - Captures 90-97% of all true AC states
  - Tracks actual load very well

- Identification of AC states
  - decision trees
  - estimated using “Random Forest”
State Predictions

[Graphs showing load, state, and probability over time]
Revealed Valuation

- Take state $r$ away in period $t$
- Get new predicted probabilities $\tilde{\pi}_t^s$
- Averaged prediction

$$\tilde{y}_t = \sum_{s \neq r} \tilde{\pi}_t^s \hat{y}_t^s$$

- Change in load is

$$\Delta y_t^{-r} = \hat{y}_t - \tilde{y}_t$$

- Revealed choices thus implicit valuation
- Estimated as a probit model
Predicted Demand Response

- Consider a situation: \((z, x)\)
- Predict probability of states (limiting distribution of MC)
- Predict quantities (Tobit)
- Predict probability of AC “on”
- Predict expected AC (controllable) load
- Predict valuation of load
- Repeat for \(n\) households
- Results in a demand resolution supply curve
AC “on” Probability

![Graph showing the probability of AC being on as a function of temperature (°F). The probability increases as the temperature increases.](image-url)
Expected AC Load
Expected Demand Response Curve
Conclusions

- Smart meter data is an emerging data source
- IOHMM can be used to detect consumption patterns
- Provides a foundation for
  - estimating demand response supply functions
  - designing contracts
  - identifying potential participants
- Know your customers, i.e. tailored products