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

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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?

Outline

Pecan Street Data

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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

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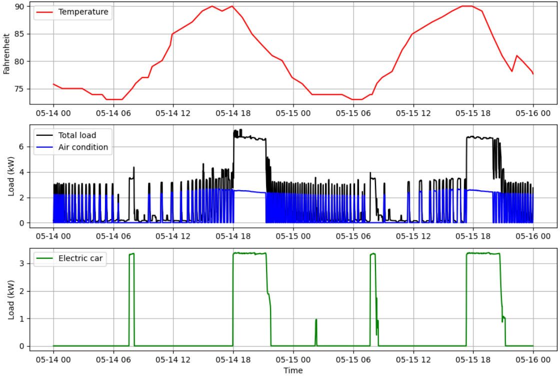
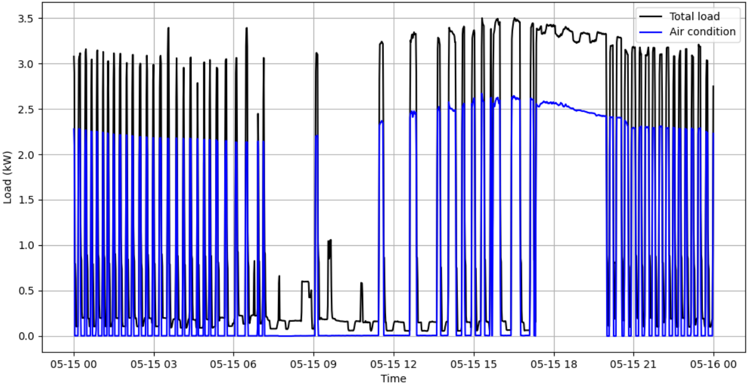
Load and Temperature



Load and HVAC



Outline

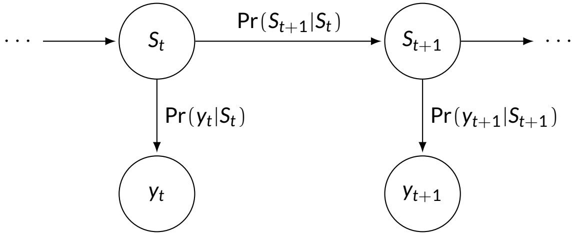
Machine Learning

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

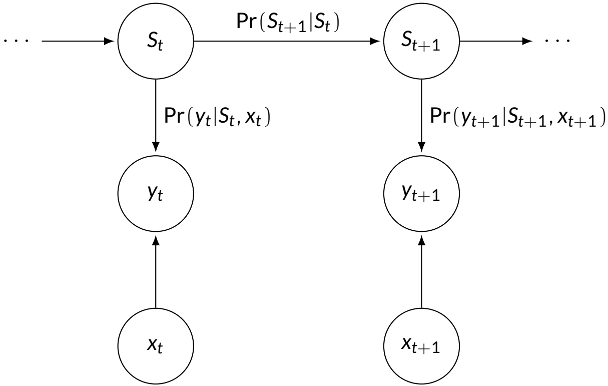
Switching Regression

- 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

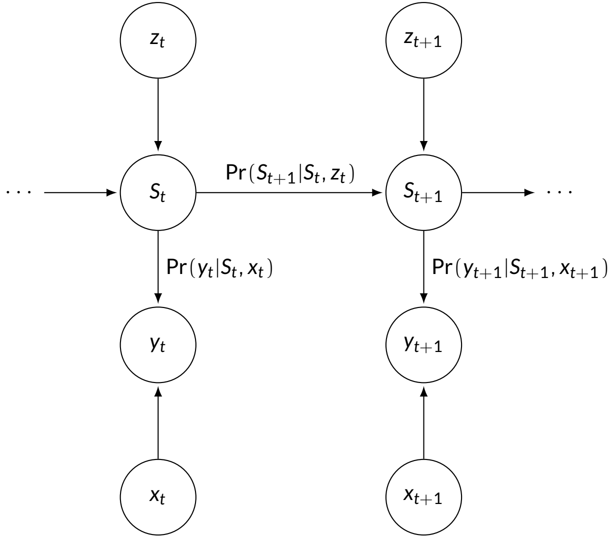
Hidden Markov Model



Output Hidden Markov Model (switching regression model)



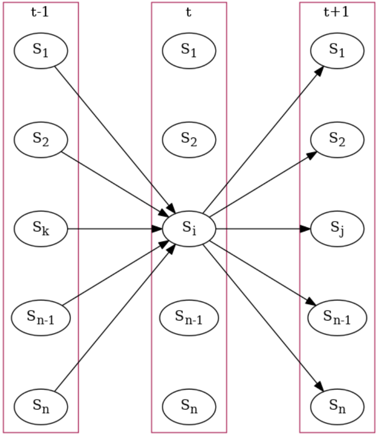
Input-Output Hidden Markov Model



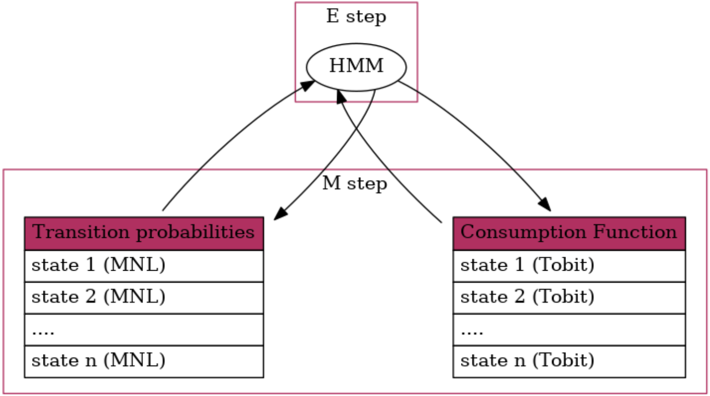
Model Estimation

- 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



EM Estimator

Python Code

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

Outline

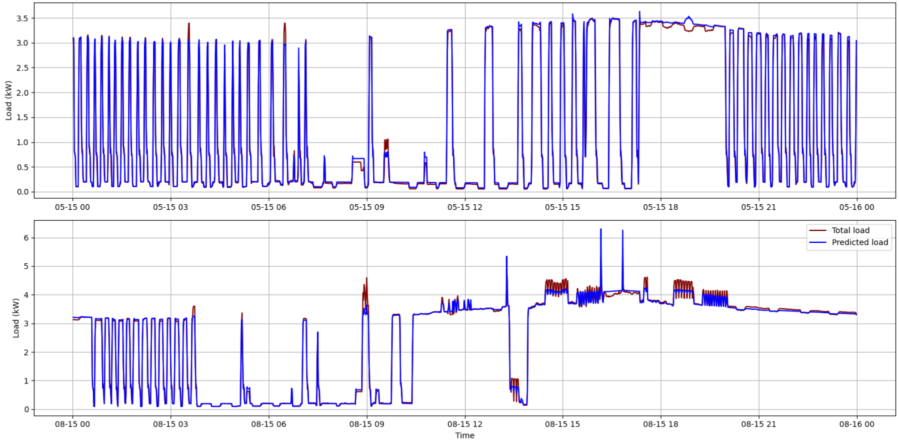
Predicted Consumption

- 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



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
- Indentification of AC states
  - decision trees
  - estimated using “Random Forest”

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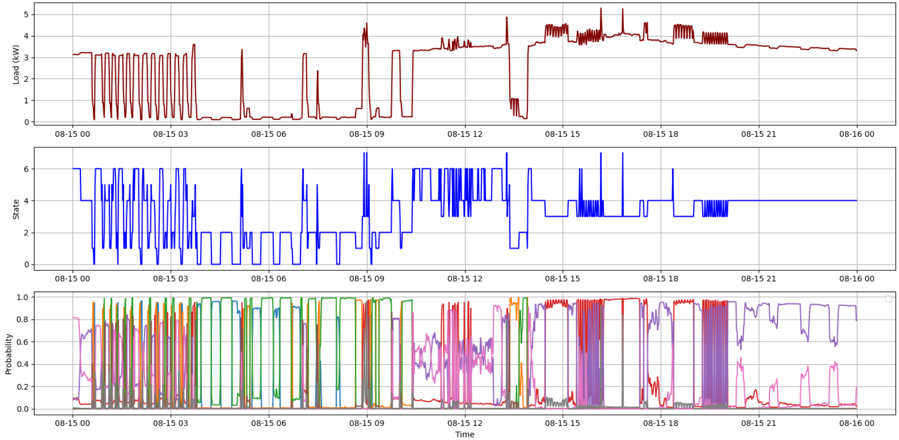
State Predictions



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

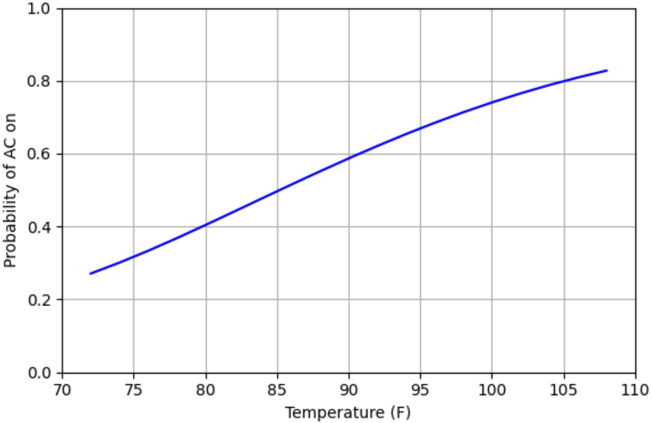
$$\Delta y_t^{-r} = \hat{y}_t - \tilde{y}_t$$

- 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



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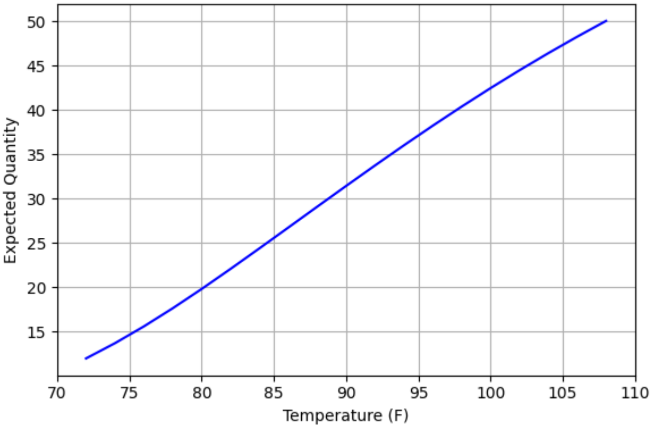
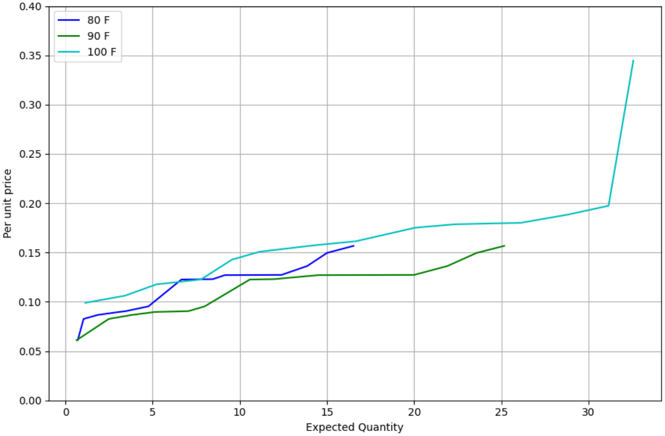
Expected AC Load



Expected Demand Response Curve



Outline

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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