Demand Response Supply Estimation with Smart Meter Data

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Energy System Transition

- The 4Ds
  - decarbonization
  - decentralization
  - digitalization
  - democratization
- Demand response among end-users
  - engage
  - activate
  - harness
- Contract design for demand response
  - consumption patterns
  - population heterogeneity

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Outline

Demand Response

- Load shifting/shedding
  - minimize impact on comfort
  - focus on (ultra) short-run
    - 5–10–15 (30) minutes
    - repeated engagement
- Applications
  - managing local grid capacity constraints (black outs)
  - bid demand flexibility into electricity markets
  - price spikes

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

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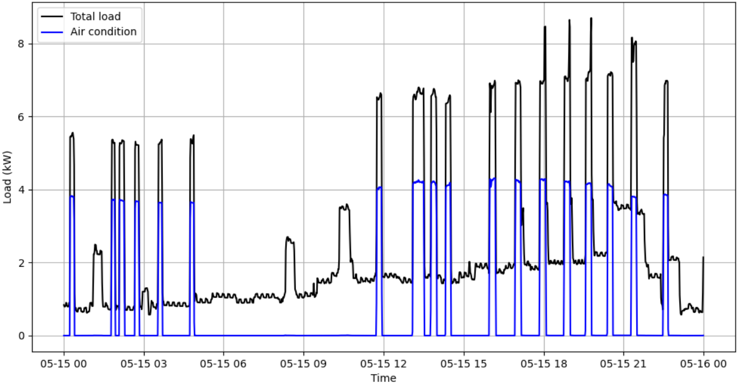
Outline

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 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

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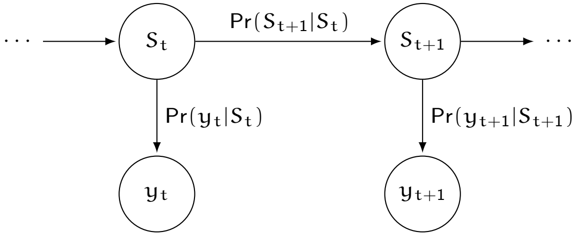
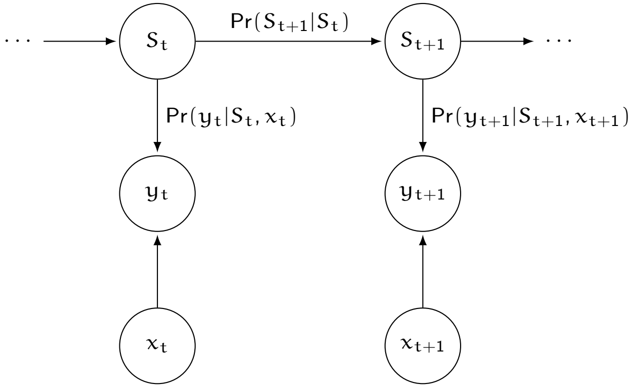
Switching Regression

- 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

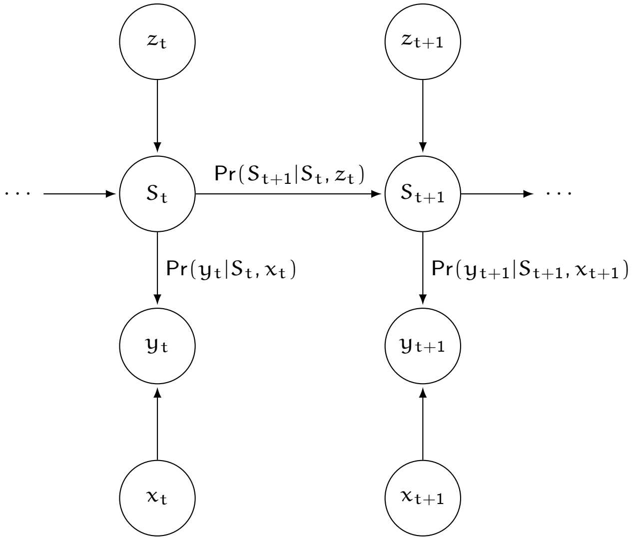
Hidden Markov Model



Output Hidden Markov Model (switching regression model)



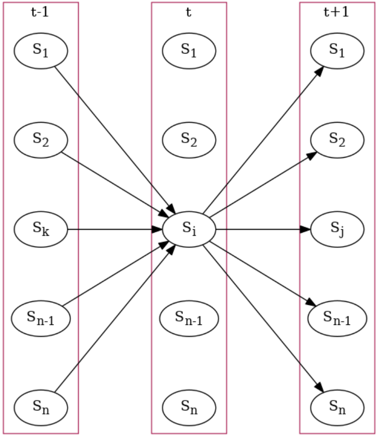
Input-Output Hidden Markov Model



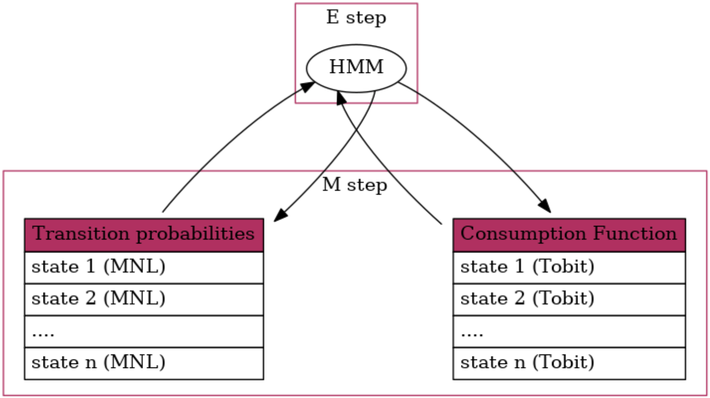
Model Estimation

- 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

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 (some 200 000 obs)
- Typically 6–9 (6) 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

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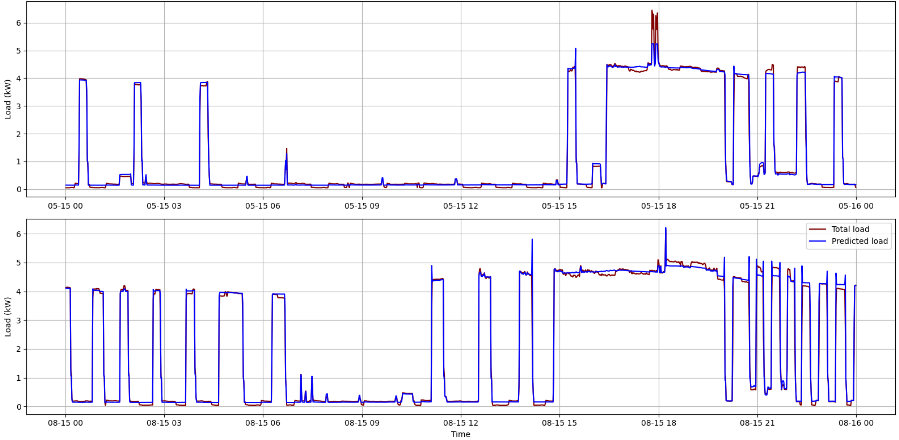
Load Prediction



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State Predictions

- AC states are clearly identifiable (for 22 houses)
  - 2–4 "AC" states
  - Captures 90-97% of all true AC states
  - Tracks actual load very well
- Indentification of AC states
  - classification
    - random forest
    - logit
  - decision trees
    - fast-and-frugal (decision tree)

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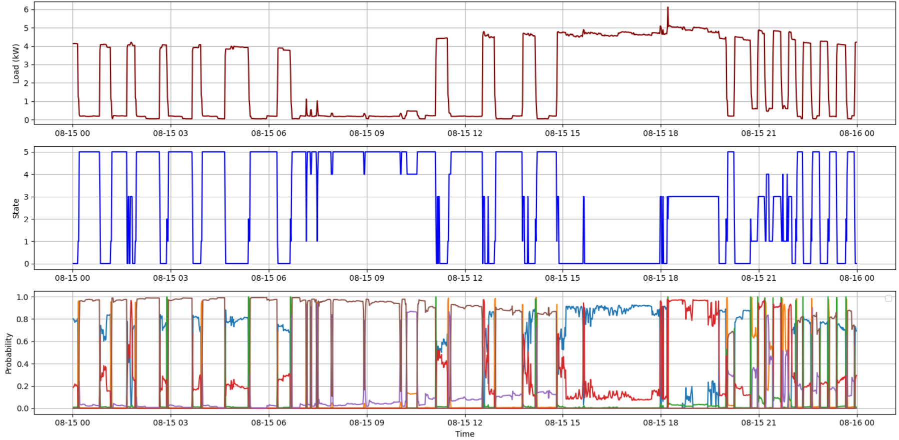
State Predictions



Revealed Valuation

- Take AC state(s) 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 with implicit valuation

$$\mathrm{WTP}(AC_t) > p_t \Delta y_t^{-r}$$

- Estimated as a probit/censored regression model (Cameron approach)

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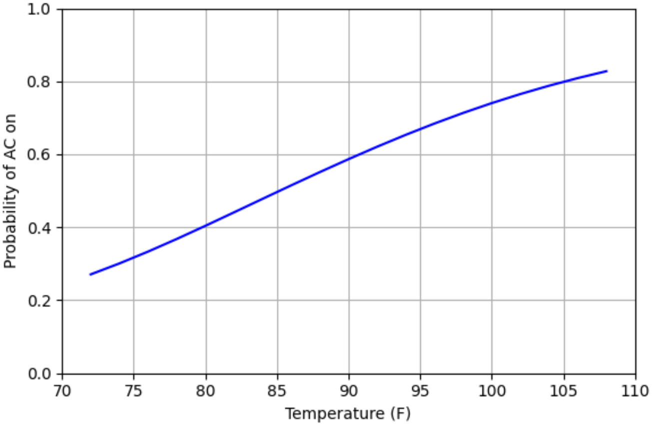
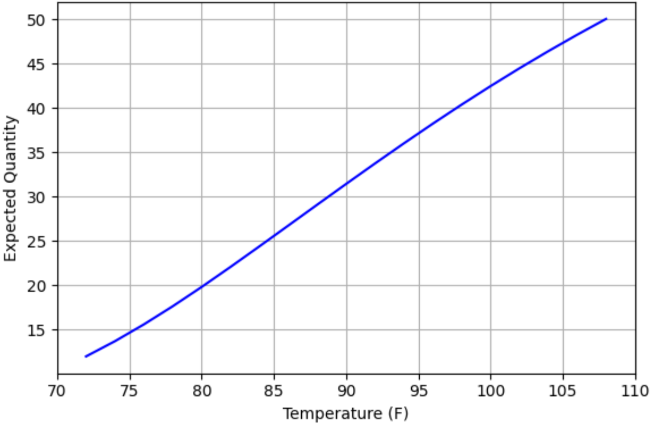
Predicted Demand Response

- 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 response supply curve

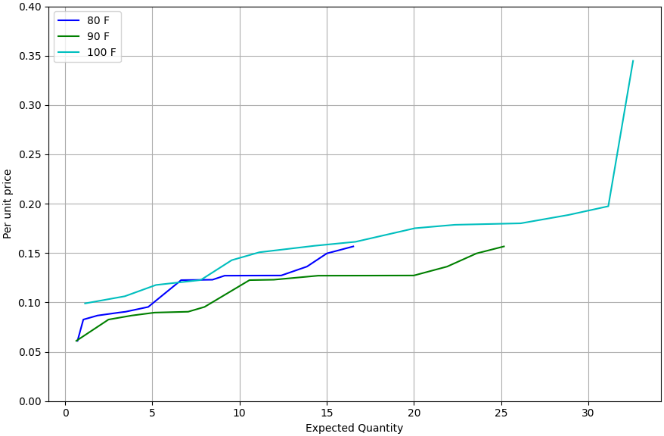
AC "on" Probability



Expected AC Load



Expected Demand Response Curve



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Conclusions

- Smart meter data is an emerging data source
- IOHMM can be used to detect consumption patterns
- Classification of states into flexible/non-flexible
- Estimate reservation prices
- Provides a foundation for
  - creating demand response supply functions
  - designing contracts
  - identifying potential participants

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