I know what you did last summer (wanted to save energy): smart meter data accurately predict household intention to enroll in energy efficiency program

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Motivation

- Behavior-based opt-in energy efficiency/demand response programs
  - Evaluation: need for control group
  - Enrollment:
    - High customer acquisition costs
    - Low enrollment rate

- Would love to predict enrollment outcome!
State of the Art

- Assume the propensity to enroll correlates with household characteristics, e.g., age, household income, education, “environmental issues” (expressed interest in environmental or wildlife issues), “green living” (model-based variable which aims to predict households that are living environmentally friendly), ...

- Devise a math model (e.g., logistic regression) to connect these characteristics to probability to enroll

- “Train” the model, i.e., estimate model parameters using household and enrollment data


Problems

- Prediction accuracy with training data: pseudo R-squared 0.035
- No testing
- Household data: availability and cost
Objectives

- Accurately predict household propensity to enroll in opt-in behavior based energy efficiency/demand response programs
- Use only data freely available to utilities/program contractors
- Validate method using field data
The Freely Available Data

- 38,524,639 residential smart meters in the US as of 2012 (www.eia.gov)
- Rich interval data embedding household appliance usage behaviors

Expected Smart Meter Deployments by State by 2015
Proposed Method (1/2)

- State-of-the-art technique (logistic regression) unsuitable
  - Problems with input data (365*24 = 8,760 data points per household)
  - Not optimal for discrimination

- Nonlinear machine learning algorithm*
  - Can handle large data arrays for input
  - Specifically designed for discrimination between 2 classes (enrolled/not enrolled)
  - Uses training, similarly to logistic regression

*Patent pending
Proposed Method (2/2)

- Black box system: input → NML algorithm → output
  - Input: 1 hour-resolution electricity consumption from a smart meter collected over ~ 1 year
  - Output: Two scores for either class (enrolled/ not enrolled)
Case Study: Description

- Fraunhofer CSE was contracted to evaluate energy saving of a new opt-in residential behavior Program.

- Program elements:
  - West-coast based
  - Several recruitment channels – local educational institutes, social media and news advertisement
  - Eligibility: must reside in certain area of a major city
  - Participants control their electricity usage by monitoring their hourly electricity consumption data
  - Significant awards for energy savings to the participating households

- No experimental control group
Field Data Description

- Pool 1: Smart meter data on ~5,600 households that enrolled in the Program (out of 470,000 eligible households, or 1.2%)
  - Hourly electricity consumption for ~18 months (including 1 year before the Program) of each household
  - Zip code of each household
- Pool 2: Smart meter data on ~32,000 households resided just outside the eligible area (still same city and microclimate zone)
  - Hourly electricity consumption for ~18 months (1 year before the Program) of each household
  - Zip code of each household
- Pool 1 seems to be similar to Pool 2
  - Socio-economic data do not differ significantly (US Census by zip code)
  - Average hourly electricity consumptions do not differ significantly
Algorithm Training

1-year smart meter data

\[
\begin{align*}
1 \times 8,760 \text{ data array for enrolled household #1} \\
1 \times 8,760 \text{ data array for enrolled household #2000} \\
1 \times 8,760 \text{ data array for not enrolled household #1} \\
1 \times 8,760 \text{ data array for not enrolled household #2000}
\end{align*}
\]

Results: Distributions of scores (1 for enrollment class, 2 for non-enrollment class) of trained algorithm for a sample of 2,000 enrolled households.
Algorithm testing

- Classify a random sample of 2,000 enrolled households and a random sample of 2,000 not enrolled households that were not used for training (testing samples)
- Repeat the process of training and testing using random samples (multiple cross-validation)

Classification Accuracy in Cross Validation, 95% Confidence Interval

<table>
<thead>
<tr>
<th>Samples used</th>
<th>Enrolled households</th>
<th>Not enrolled households</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training samples</td>
<td>92.4±1.1 %</td>
<td>91.7±1.3 %</td>
</tr>
<tr>
<td>Testing samples</td>
<td>91.2±1.1 %</td>
<td>90.5±1.4 %</td>
</tr>
</tbody>
</table>
Objectives

✓ Accurately predict household propensity to enroll in opt-in energy efficiency/demand response programs
✓ Use only data freely available to utilities/program contractors
✓ Validate method using field data
Potential Implementation

- Sample of ~1,000 households that enrolled – obtain interval pre-program data for ~ 1 year
- Sample of ~1,000 households that did not enroll – obtain interval pre-program data for ~ 1 year
- Train the algorithm (“push button”)
- Obtain pool of candidate households (interval data for each household)
- Calculate which households are likely to enroll (“push button”)
Interesting Observations

- Possible correlation between propensity to enroll and average electricity consumption?

  Average hourly electricity consumption vs. propensity score for a sample of 2,000 enrolled households

- ~9% are likely to enroll but actual enrollment rate 1.2% ??
Open Questions

- Our method worked well (enrollment prediction with 90% accuracy) for given region/program. Will it work elsewhere?
- Can enrollment data from one program be used as proxy for another program in the same region?
- Can NML algorithm, trained on data from one region, be used for another region?
- What are requirements to the region (e.g., size, homogeneity)?
- Targeted advertisement for those likely to enroll?
I know what you did last summer!
Additional materials

Hourly electricity consumption data for September 21-23, 2011, averaged over groups

- PSM = non-experimental control group built using propensity score from candidate households
- Energy-matched = non-experimental control group built by matching average energy between treatment and candidate households