Creating a detailed energy breakdown from *just* the monthly electricity bill

Nipun Batra, Amarjeet Singh, Kamin Whitehouse
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## Monthly electricity bill

### Ontario Residential Monthly Bill Statement

**Account Number**
123 456 789 101 2345 0

**Meter Number**
1234567

### Your Electricity Charges

<table>
<thead>
<tr>
<th>Description</th>
<th>Amount</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electricity</td>
<td>$78.00</td>
</tr>
<tr>
<td>Delivery</td>
<td>$46.00</td>
</tr>
<tr>
<td>Regulatory Charge</td>
<td>$5.00</td>
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<tr>
<td>Debt Retirement Charge</td>
<td>$6.00</td>
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<tr>
<td>H.S.T.</td>
<td>$17.00</td>
</tr>
<tr>
<td><strong>Ontario Clean Energy Benefit</strong></td>
<td><strong>$(15.00)</strong></td>
</tr>
<tr>
<td><strong>(10 per cent off applicable electricity charges and taxes)</strong></td>
<td></td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>$137</strong></td>
</tr>
</tbody>
</table>
Monthly electricity bill

Ontario Residential Monthly Bill Statement

Account Number
123 456 789 101 2345 0

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Your Electricity Charges

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20 kWH
120 kWH
10 kWH
Obtaining energy breakdown

Sensor per appliance

Smart meter based energy disaggregation
Intuition
Approach overview

- 20 kWh
- 30 kWh
- 50 kWh
- 20 kWh
- 80 kWh
- 90 kWh
- 60 kWh
- 80 kWh
- 10 kWh
- 20 kWh
- 10 kWh
- 10 kWh
Approach overview

- Refrigerator: 20 kWh
- Air conditioner: 30 kWh
- Washing machine: 50 kWh
- House: 20 kWh
- Air conditioner: 80 kWh
- Washing machine: 60 kWh
- House: 80 kWh
- Air conditioner: 10 kWh
- Washing machine: 10 kWh
- House: 10 kWh
Approach overview

- 20 kWh
- 80 kWh
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- 10 kWh
- 10 kWh
Approach overview

- Refrigerator: 20 kWh
- Air conditioner: 80 kWh
- Washing machine: 10 kWh
- Lighting: 50 kWh
- HVAC system: 60 kWh
Approach overview

20 kWh

50 kWh
Approach overview

35 kWh

20 kWh

50 kWh
Approach overview
Approach overview

70 kWh

60 kWh  80 kWh
Approach overview

- 35 kWh
- 70 kWh
- 20 kWh
Features

<table>
<thead>
<tr>
<th>Derived</th>
<th>Area, #occupants, #rooms, Aggregate home energy in Jan, Feb,..December</th>
<th>Variance, range, percentiles, ratio min to max., skew, kurtosis</th>
</tr>
</thead>
</table>
Step 1: Feature selection

Feature selection algorithm

- Area, #occupants, #rooms
- Aggregate home energy in Jan, Feb,..December
- Variance, range, percentiles, ratio min to max., skew.

20 kWh  40 kWh  30 kWh
### Step 11: Matching

<table>
<thead>
<tr>
<th>Train homes</th>
<th>Feature 1</th>
<th>Feature 2</th>
<th>Overall</th>
<th>Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test home</td>
<td>..</td>
<td>..</td>
<td>0.3</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>..</td>
<td>0.2</td>
<td>0.4</td>
<td>4</td>
</tr>
<tr>
<td></td>
<td>..</td>
<td>0.05</td>
<td>0.1</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>0.1</td>
<td>0.1</td>
<td>0.2</td>
<td>2</td>
</tr>
</tbody>
</table>

Top-K neighbours
Step III: Prediction

Test home

Combining function

Top-k Neighbours

20 kWh

18 kWh

22 kWh
## Evaluation - Dataset

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Region</th>
<th>#Homes</th>
<th>Dataset duration</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data port</td>
<td>Austin, TX</td>
<td>57</td>
<td>12 months</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>HVAC</th>
<th>Fridge</th>
<th>Lighting</th>
<th>Dryer</th>
<th>Dish washer</th>
<th>Washing machine</th>
</tr>
</thead>
<tbody>
<tr>
<td>31</td>
<td>21</td>
<td>12</td>
<td>32</td>
<td>26</td>
<td>16</td>
</tr>
</tbody>
</table>
Evaluation - Baseline

Factorial Hidden Markov Model (FHMM) [AISTATS 2012]

Latent bayesian melding (LBM) [NIPS 2015]
Evaluation- Metric

Absolute error = |Predicted energy - Actual Energy|

Normalised Absolute error = Absolute error/Actual Energy

Normalised percentage error = Normalised absolute error \times 100

Percentage accuracy = 100 - Normalised percentage error
## Evaluation- Experimental setup

<table>
<thead>
<tr>
<th>Cross-validation</th>
<th>Optimising #neighbours and feature selection</th>
<th>Feature ranking</th>
</tr>
</thead>
<tbody>
<tr>
<td>Leave one out</td>
<td>Nested cross validation</td>
<td>Random Forest</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th># HMM states</th>
<th># appliances in model</th>
<th>Training on</th>
<th>Temporal resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>6</td>
<td>Entire data</td>
<td>15 min</td>
</tr>
</tbody>
</table>
Result

![Energy Accuracy Graph](image)

- **FHMM**
- **LBM**
- **Gemello**

**Devices**:
- HVAC
- Fridge
- Washing machine
- Lights
- Dryer
- Dishwasher

**Accuracy (%)** (Higher is better)
Result-II

![Bar chart showing energy accuracy for different appliances:
- HVAC
- Fridge
- Washing machine
- Lights
- Dryer
- Dish washer

Y-axis: Energy Accuracy (%) (Higher is better)
X-axis: Appliances
Legend:
- LBM (15 min)
- LBM (2 min)
- Gemello]
Result-scalability
Predicting for different region
Transformation strategies

\[
\begin{align*}
\text{HVAC energy in R1} & \times \frac{\# \text{ Degree days in R2}}{\# \text{ Degree days in R1}} & \text{HVAC energy in R2} \\
200 \text{ kWh} & & 250 \text{ kWh}
\end{align*}
\]

\[
\begin{align*}
\text{Appliance (A) energy in R1} & \times \frac{\text{Mean proportion of A in R2}}{\text{Mean proportion of A in R1}} & \text{Appliance (A) energy in R2} \\
10 \text{ kWh} & & 1.5 \text{ kWh}
\end{align*}
\]
Result cross region training

Energy Accuracy(%) (Higher is better)

- Fridge
  - Regional average
  - NILM
  - EnerScale

- HVAC
  - Regional average
  - NILM
  - EnerScale

- Washing machine
  - Regional average
  - NILM
  - EnerScale
Limitations & Ongoing work

1. Finding anomalous test homes
2. Adapting to people change behaviour
Conclusions

1. Gemello- scalable and accurate energy breakdown
2. Transformation- scale across regions
3. Potential to be rolled off as a service today