The Wild West of Evaluation?

Comparing Methods of Outlier Detection in Consumption Analyses

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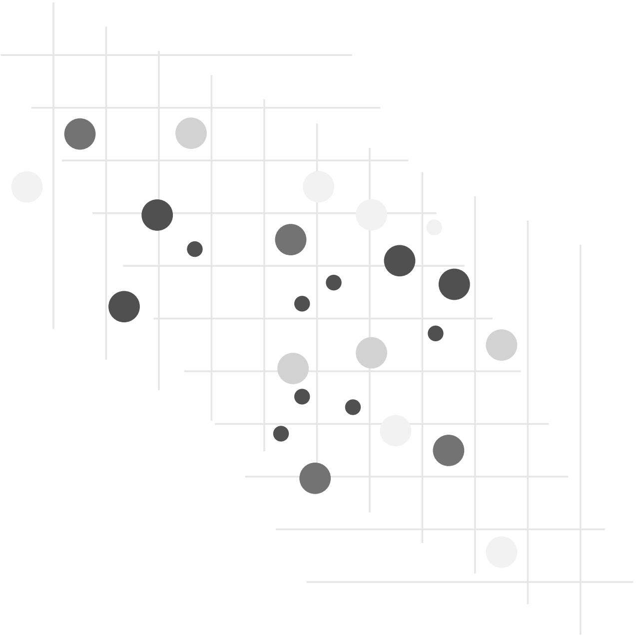
What are outliers in consumption analyses?



- Outliers in consumption analyses are individuals that exhibit extremely large changes in energy use between the pre- and post-treatment periods

- Problem: there aren't strong industry-standard guidelines for identifying and handling consumption outliers

A few questions about outliers…

Why do outliers matter?

- Outliers can bias results if the extreme changes in consumption aren't the result of the energy efficiency intervention.

What causes outliers?

- Outliers can occur due to faulty meters, household characteristics, occupancy changes, or abnormally large true changes in consumption.

How do we determine what an outlier is?

- Good question! More on that in the next slide.

How have other studies determined outliers?

Typically, outlier detection approaches employ a few different strategies:

- Numeric thresholds
  - E.g., removing individuals with changes in consumption over 90% in either direction
- Variance-based thresholds
  - E.g., removing individuals with changes in annual consumption more than three standard deviations from the mean
- Percentile thresholds
  - E.g., removing individuals with changes in annual consumption greater than the 99^{th} percentile or less than the 1^{st} percentile
- A combination of these approaches

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The approach

Apply different strategies of outlier detection and removal to a real-world consumption analysis and compare the results with each approach

In each case, weather-normalized consumption based on the degree day points with the highest explanatory power (56°F for heating and 70°F for cooling) and then compared the change in consumption between the pre- and post-treatment periods

Study information

- Client: utility in the southern United States
- Study population: 23,000 accounts with 15-minute interval AMI data
- Program type: residential single-family home retrofit
- Program period: January 2017 to January 2020

What strategies did we use?

We applied each of the major outlier identification strategies and compared them along with the dataset with outliers

For each approach, we employed multiple threshold levels:

- Numeric thresholds: remove accounts with changes over 50%, 70%, or 90% of pre-treatment consumption

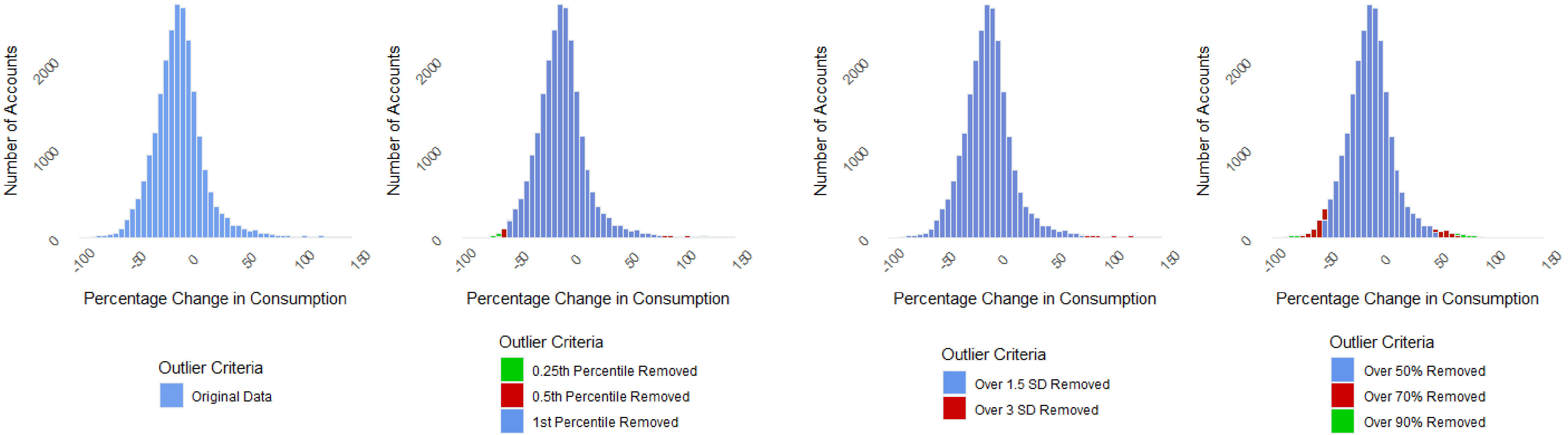
- Variance-based thresholds: remove accounts with changes in consumption that were 1.5 or 3 standard deviations above or below the mean

- Percentile thresholds: remove the top and bottom 0.25th, 0.5th, or 1st percentiles

Outlier impact on summary statistics

Outlier Method	Records Retained	Records Removed	Percent Removed	Change in Consumption (%)				
				First Quartile	Median	Third Quartile	Mean	Std. Dev.
None	23,042	-	0	-21.7	-9.3	2.6	-7.0	55.9
Over 50%	21,937	1,105	4.8	-21.0	-9.3	1.8	-9.0	18.2
Over 70%	22,690	352	1.5	-21.9	-9.5	2.0	-9.2	20.6
Over 90%	22,850	192	0.8	-21.9	-9.5	2.2	-8.9	21.7
Over 1.5 SD	22,786	256	1.1	-21.9	-9.5	2.1	-9.1	21.1
Over 3 SD	22,990	52	0.2	-21.8	-9.3	2.5	-8.1	23.8
Percentile 0.25th	22,926	116	0.5	-21.6	-9.3	2.5	-8.0	23.4
Percentile 0.5th	22,810	232	1.0	-21.6	-9.3	2.4	-8.2	22.2
Percentile 1st	22,580	462	2.0	-21.4	-9.3	2.2	-8.5	20.6

Outlier impact on consumption change distribution



Program savings under different outlier regiments

Outlier Method	Avg. Pre-Period Consumption (kWh)	Total Pre-Period Consumption (kWh)	Total Post-Period Consumption (kWh)	Avg. Raw Savings as a percent of pre-period consumption	Avg. Modeled Savings as a percent of pre-period consumption*
None	15,145	348,978,471	311,873,350	9.2	7.3
Over 50%	15,356	336,856,502	300,799,761	8.9	7.7
Over 70%	15,267	346,399,637	307,608,258	9.1	7.9
Over 90%	15,223	347,841,439	309,155,737	8.1	7.8
Over 1.5 SD	15,246	347,389,981	308,331,930	8.0	7.9
Over 3 SD	15,170	348,766,001	311,072,491	8.2	7.5
Percentile 0.25th	15,178	347,977,158	310,801,686	8.5	7.4
Percentile 0.5th	15,204	346,803,543	309,761,329	9.2	7.4
Percentile 1st	15,249	344,314,722	307,508,530	8.9	7.4

*All regression coefficients associated with post-period were statistically significant

Conclusions, Next Steps, and Continued Research

Outlier methodologies can make differences in savings consumptions, but only on the margins

- Understanding and retaining outliers may be more important in studies involving performance incentives or those with smaller populations

- With AMI data and machine learning, identifying within-subject outliers could be useful in maximizing the number of participants retained

- Ultimately, evaluators, implementers, and utilities must weigh whether the gains in accuracy are worth the added effort, cost, and expertise required for more rigorous outlier analyses