



August 13-14, 2025 | Des Plaines, Illinois

Improving safety with analytics to identify upsets in millions of AMI readings

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AMI Background

- AMI: advanced metering infrastructure
- AMI components:
 - Smart meters
 - Communication network
 - Data management system
 - User interface

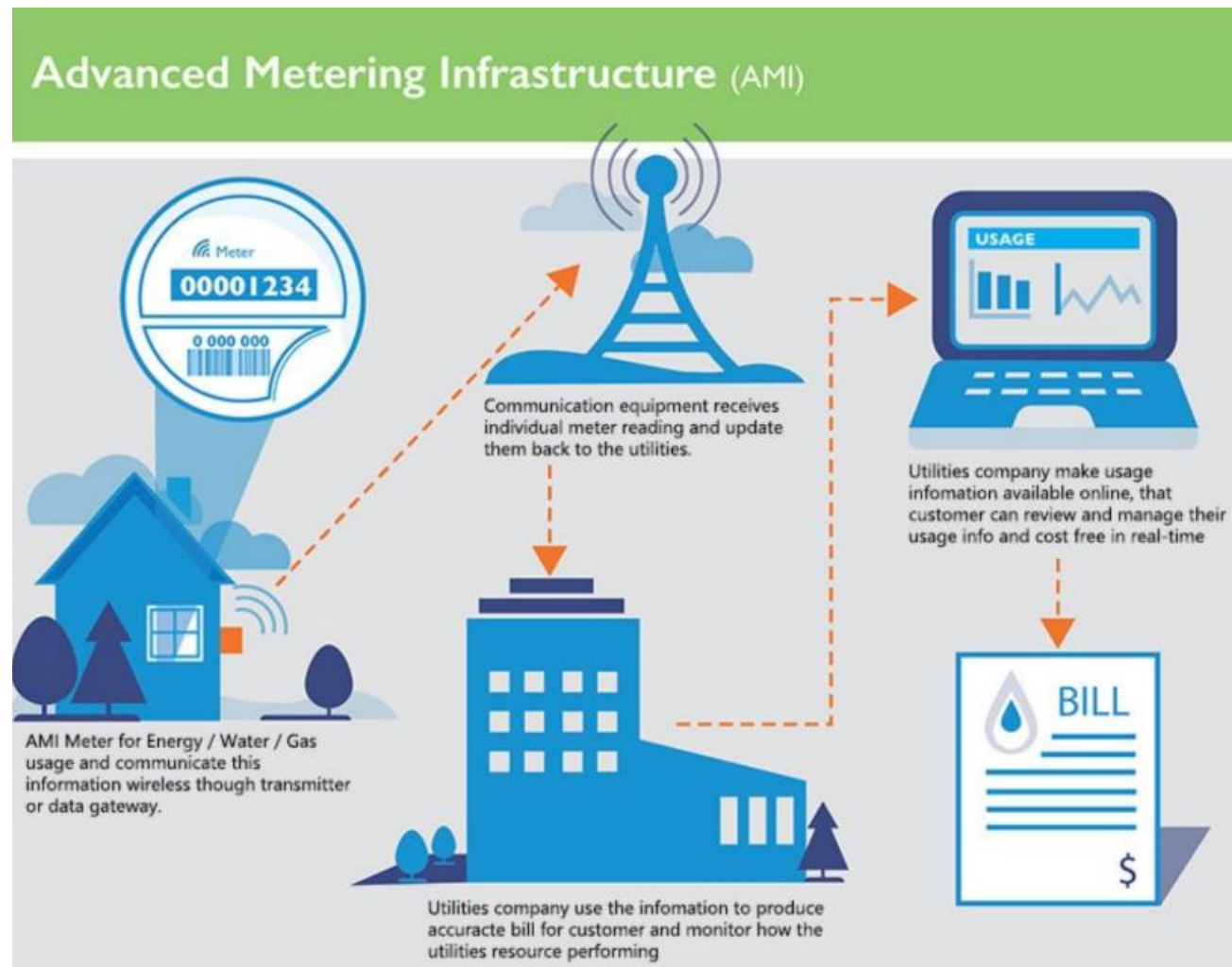


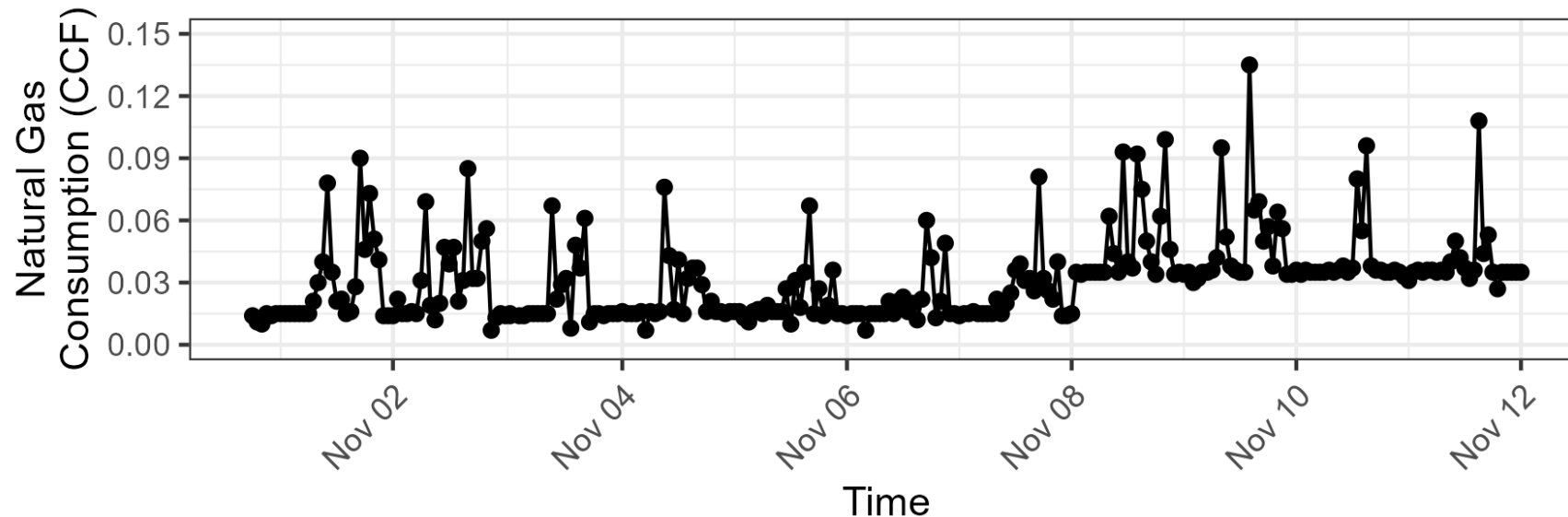
Image credit: Fort Hays State University

Identifying Anomalous Consumption

Research questions:

1. Can we use AMI data to identify upset conditions via anomalous gas usage patterns to improve safety?
2. Can we improve upon existing approaches for identifying upset conditions via usage anomalies?

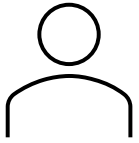
Simulated Anomalous Consumption from Real Customer



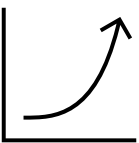
Principles of Anomaly Detection Algorithm



- Ability to tune the algorithm
 - Most readings are not anomalous
 - Sensitivity can be adjusted to the operator's tolerance



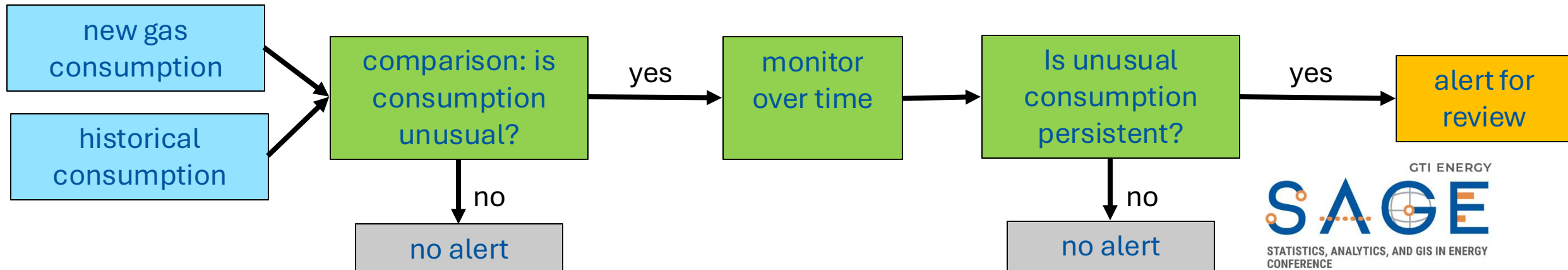
- Utilize individual customer's history
- Common types of consumption anomalies to detect:
 - Low and slow: consumption is at a low level but over a long period of time; indicative of valve left open or slow leak
 - High and fast: consumptions is at a high level (hopefully for a short period of time); indicative of large leak or unexpected consumption



Change Point Detection

In statistical terms: Is there a change point in the consumption time series?

1. Compare gas consumption value to historical consumption
2. Determine if usage is "unusual"
3. Monitor "unusual-ness" over time
4. Flag consumption for review if unusual-ness is big or persistent



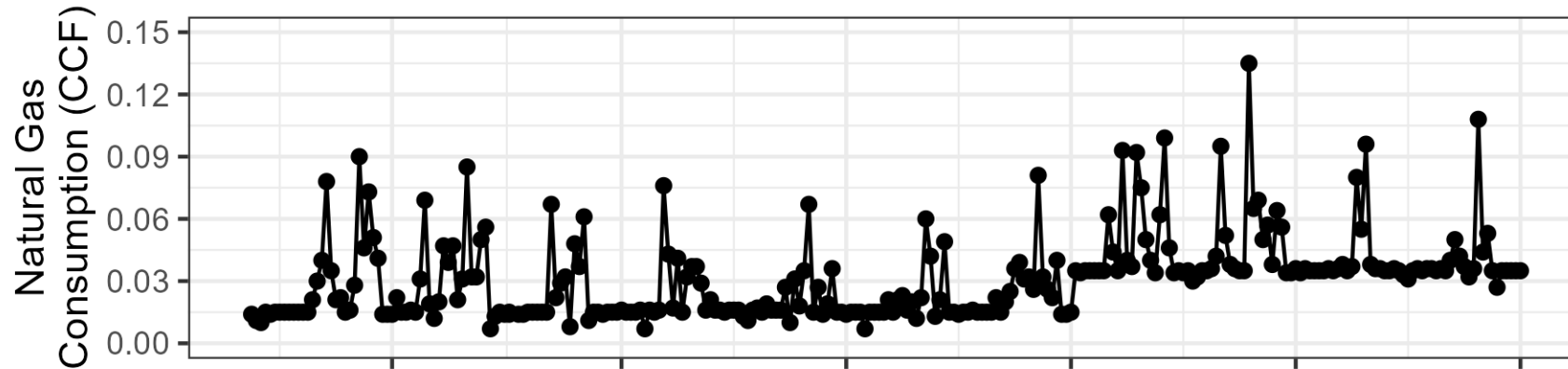


Cumulative Sum for Anomaly Detection

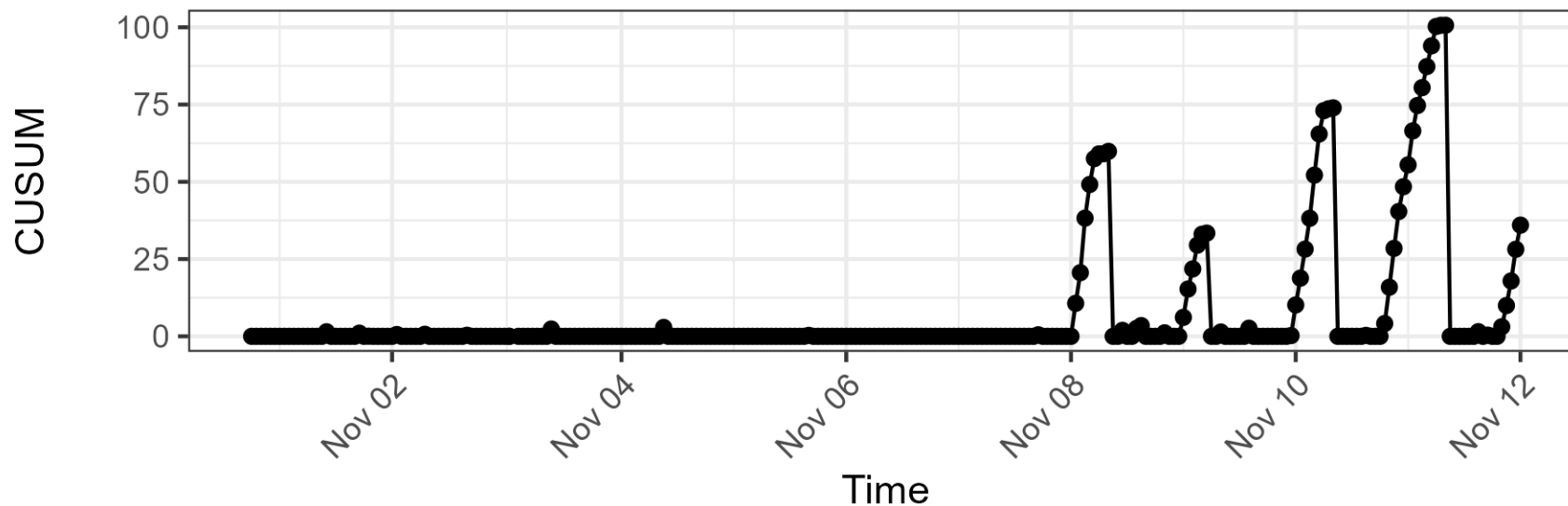
- CUSUM: cumulative sum control chart, a statistical method to detect change points
- Works by cumulatively summing deviations of data from an expected value
- Cumulative sum will begin to drift when a sustained change in the expected value occurs
- The challenge lies in defining the following:
 - Expected consumption (historical usage)
 - Threshold for classifying individual deviations from expected as "unusual"
 - Threshold for accumulation of unusual deviations
 - Threshold for persistence of deviations across time

CUSUM Chart Example

Simulated Anomalous Consumption from Real Customer

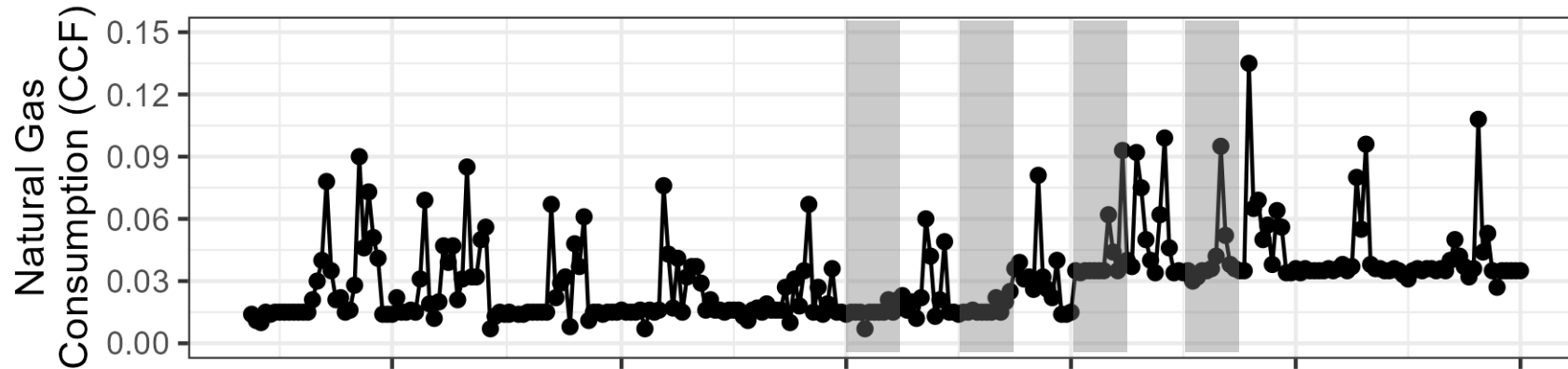


Cumulative Sum of Time Series with Alerts

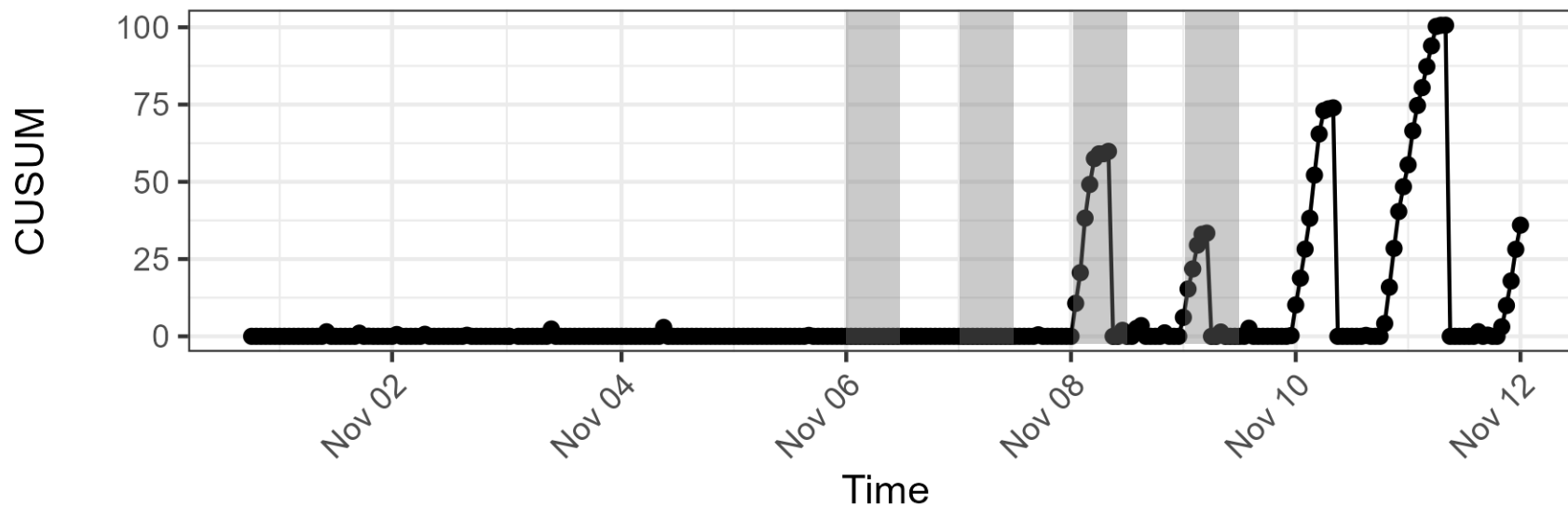


CUSUM Chart Example

Simulated Anomalous Consumption from Real Customer



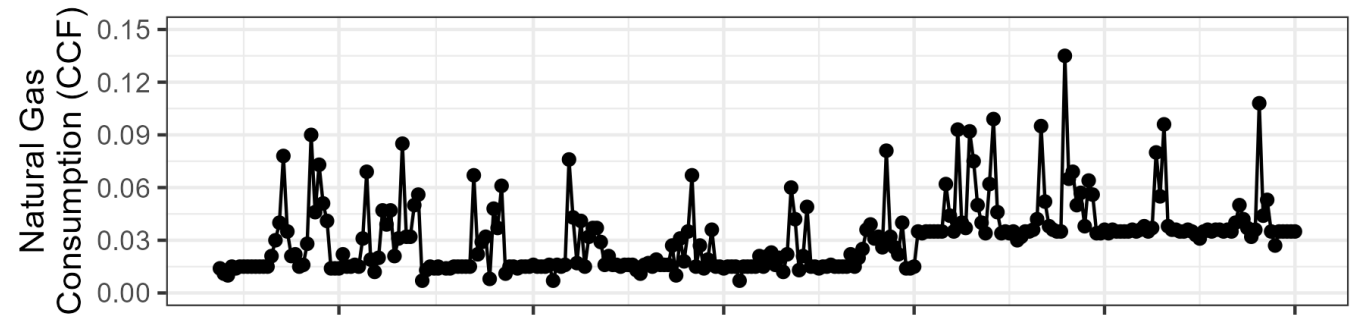
Cumulative Sum of Time Series with Alerts



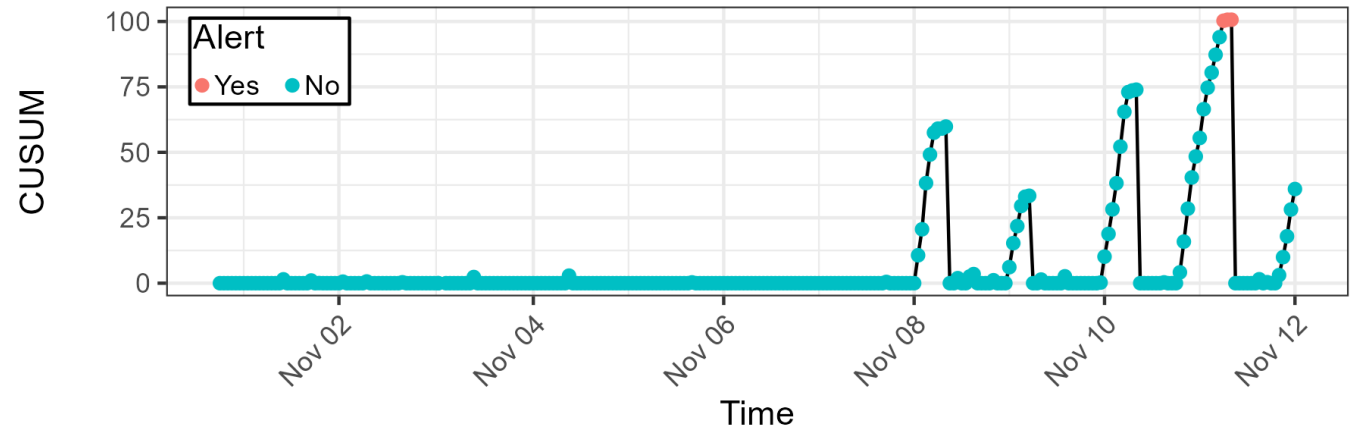
Simulated Leak

- CUSUM begins to rise when anomalous consumption starts
- Alert not initially triggered due to parameters set but does detect anomalous consumption

Simulated Anomalous Consumption from Real Customer

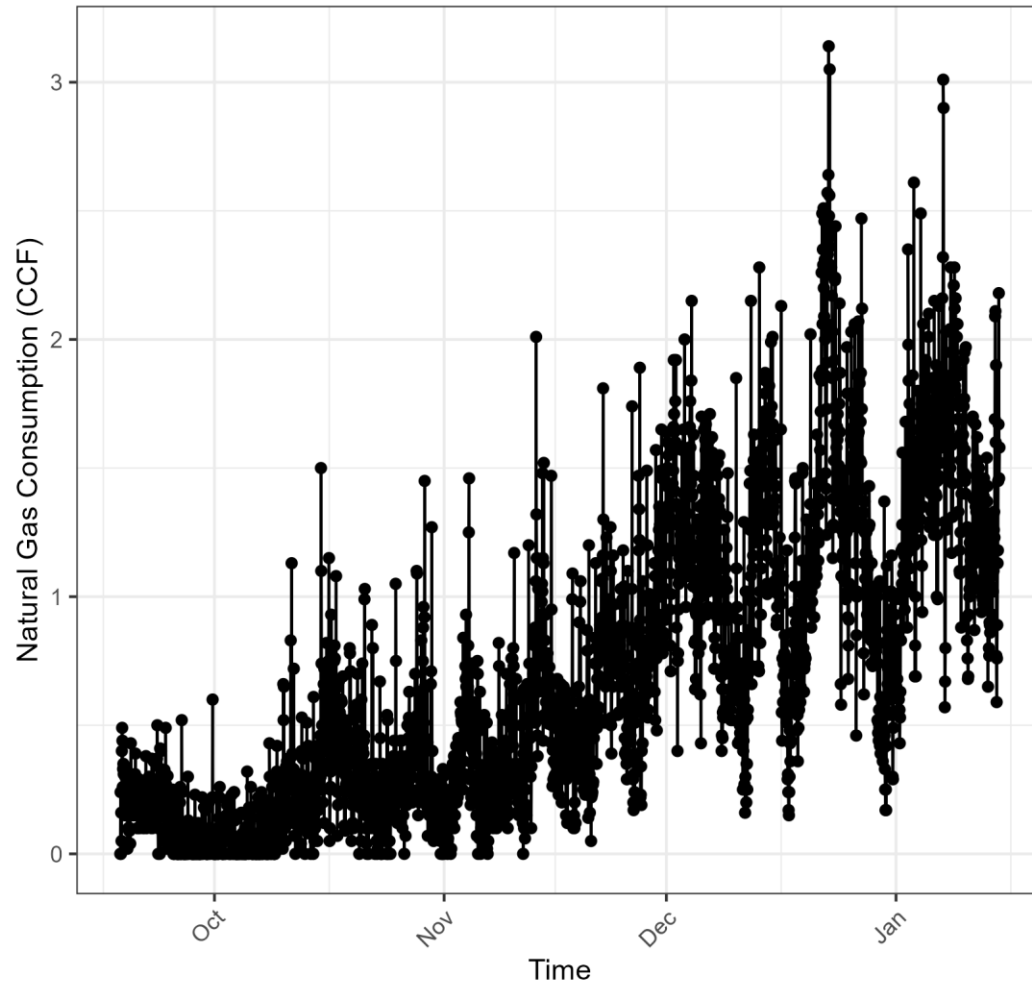


Cumulative Sum of Time Series with Alerts

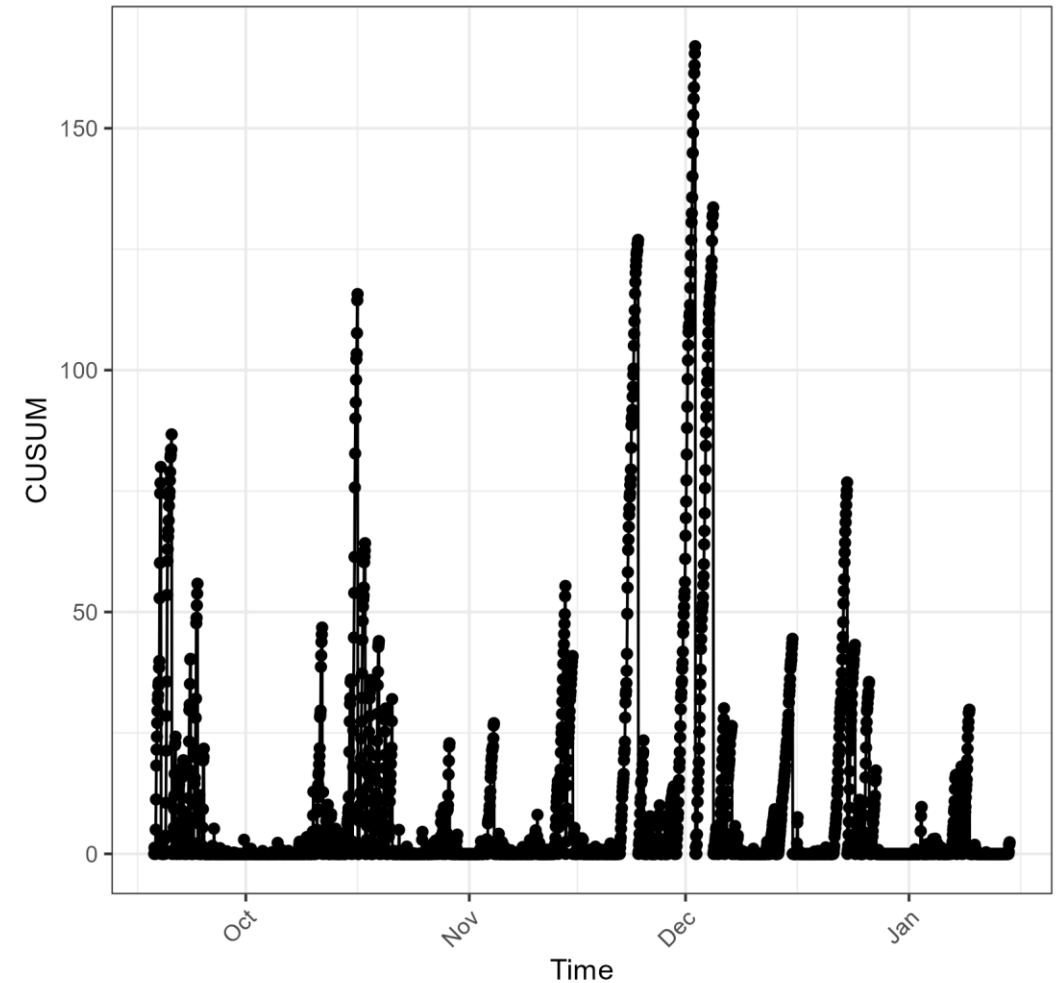


Consumption and CUSUM Time Series

Time series of customer gas usage

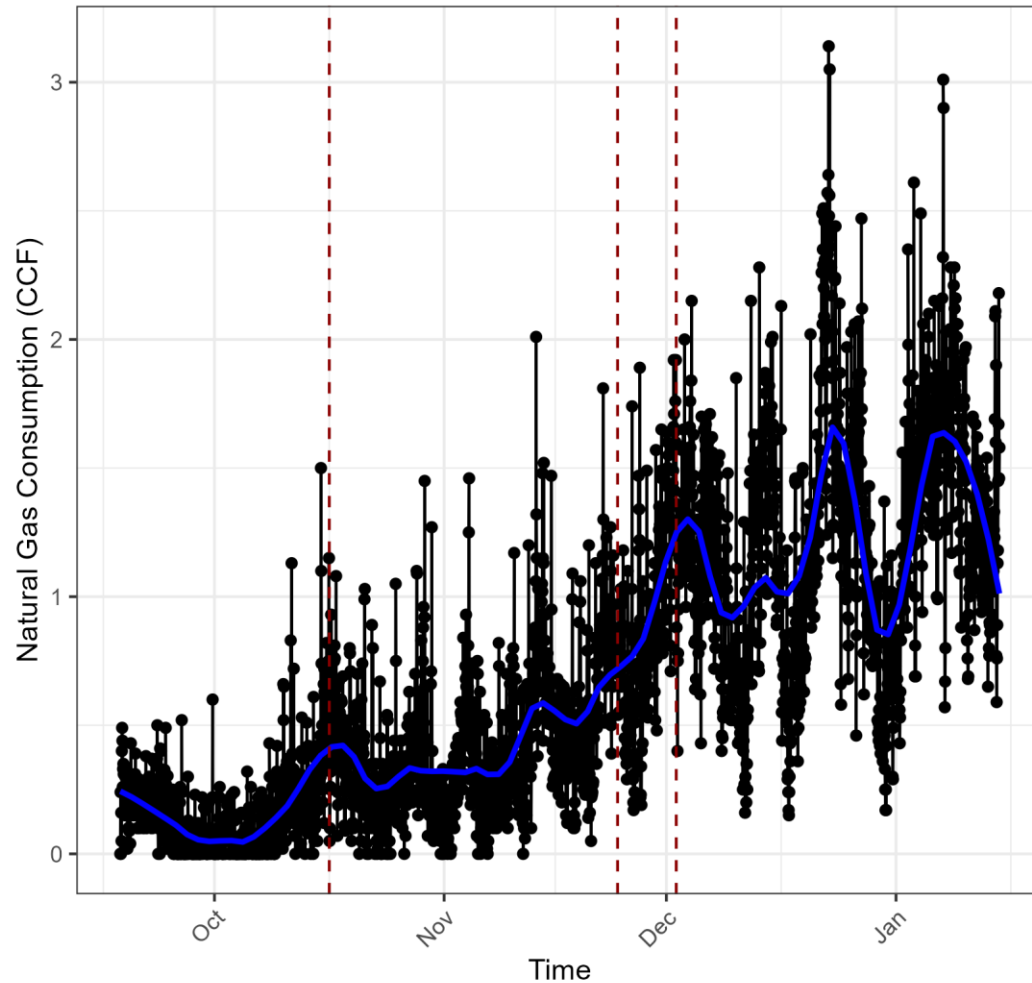


Cumulative sum of time series

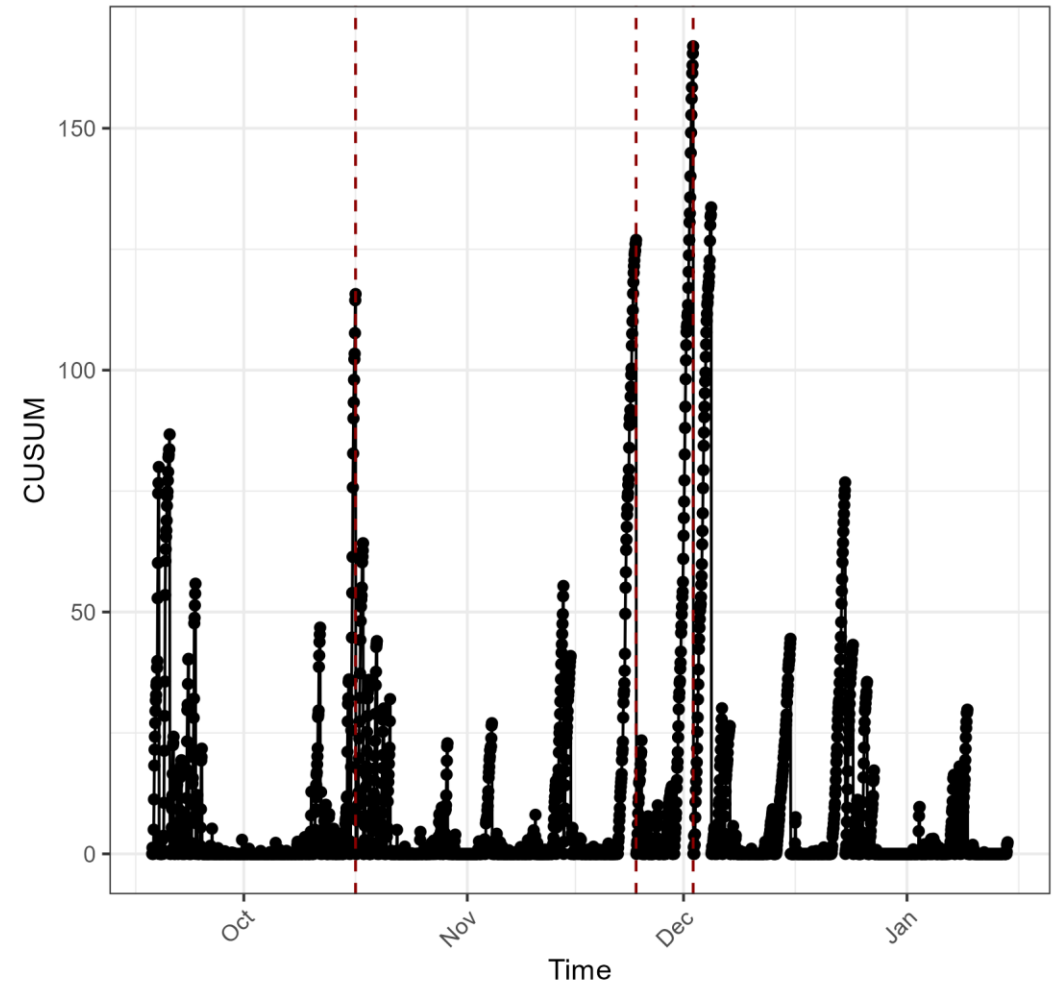


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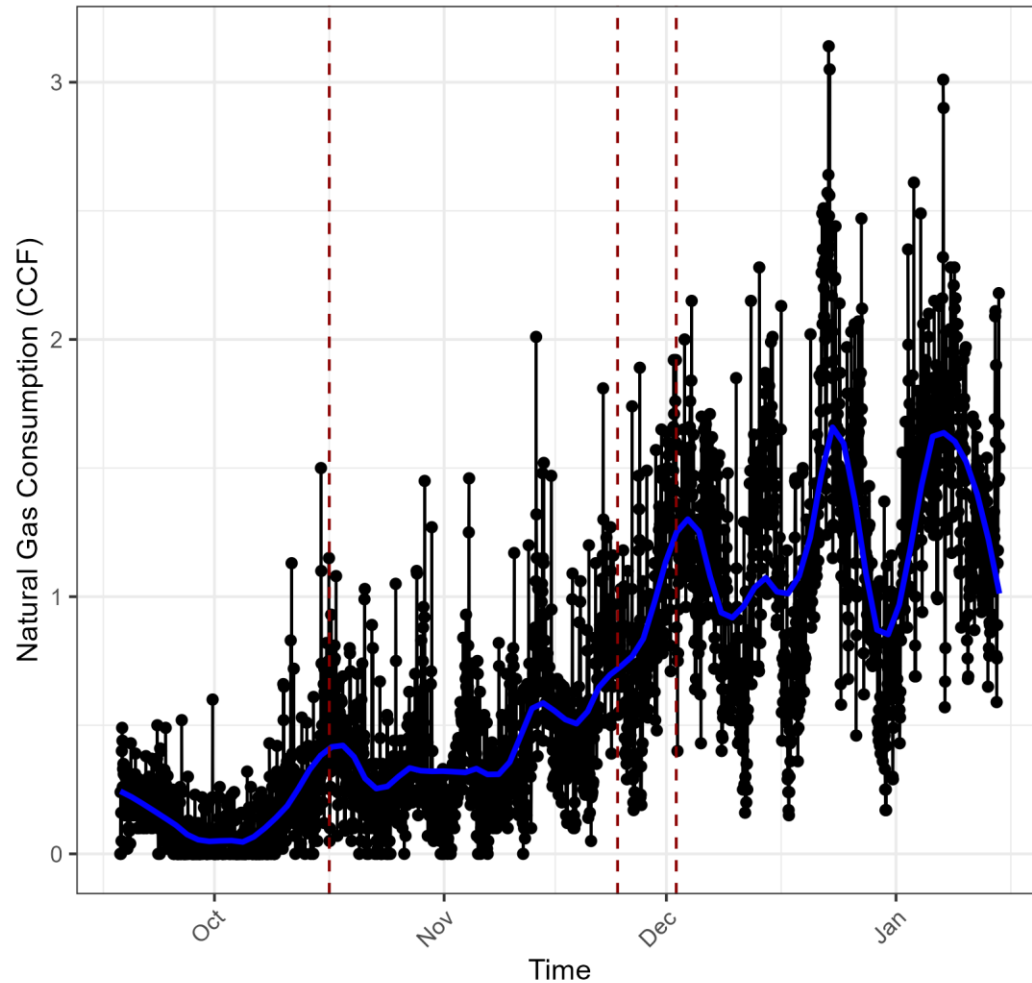


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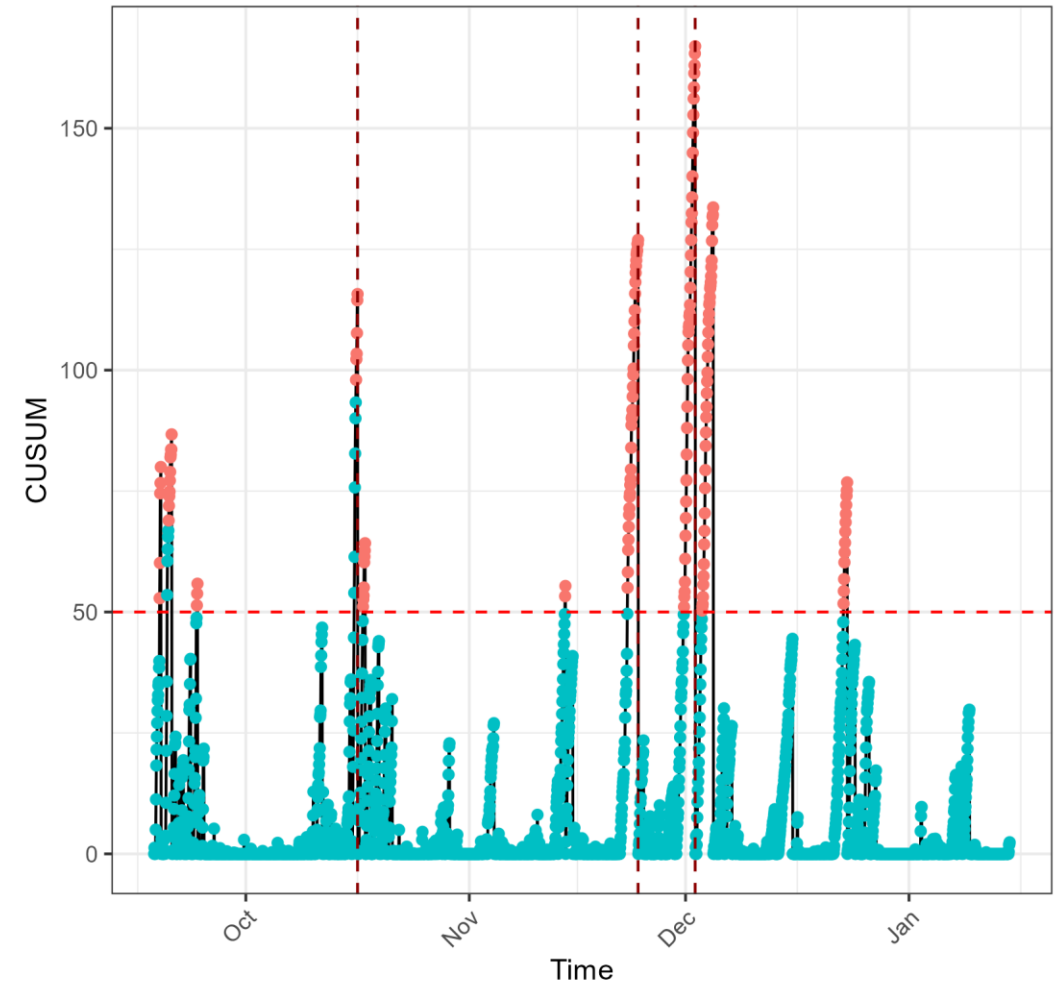


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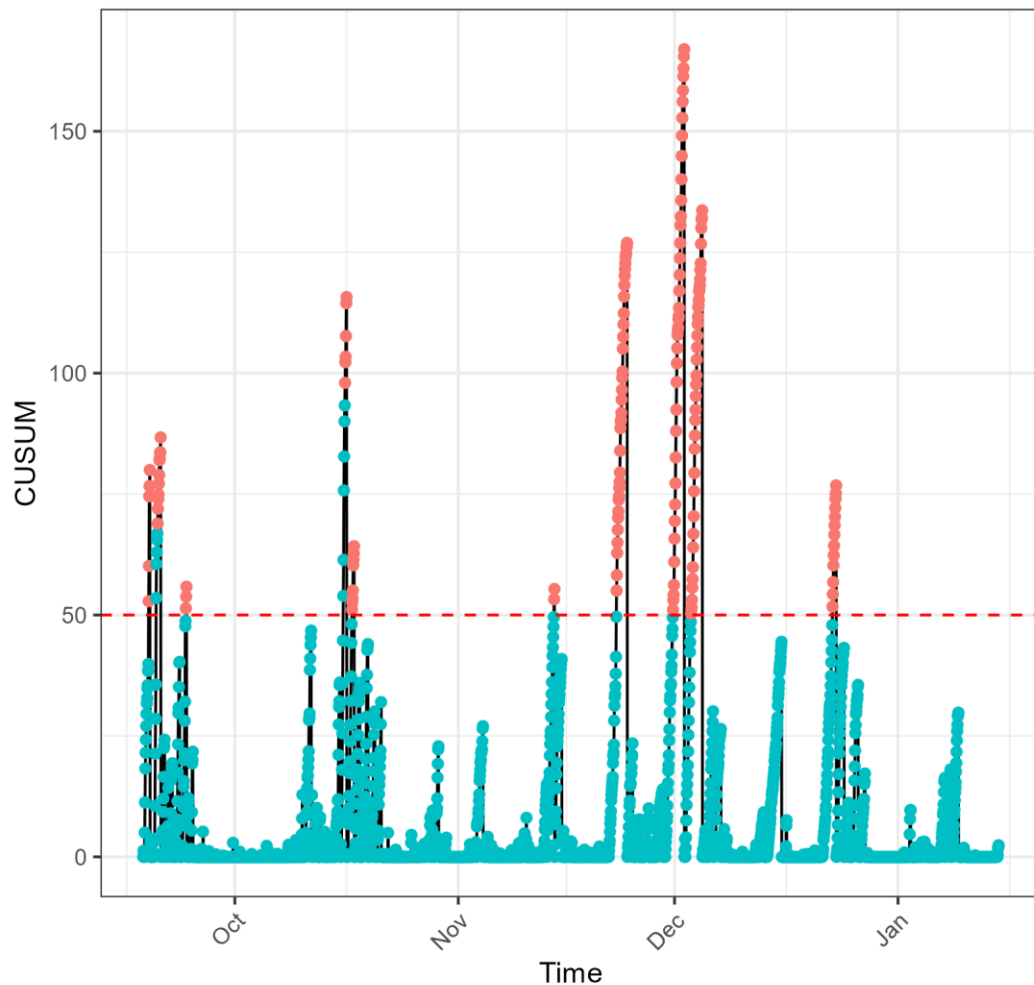


Cumulative sum of time series with alerts



Tuning CUSUM Thresholds

Cumulative sum of time series with alerts

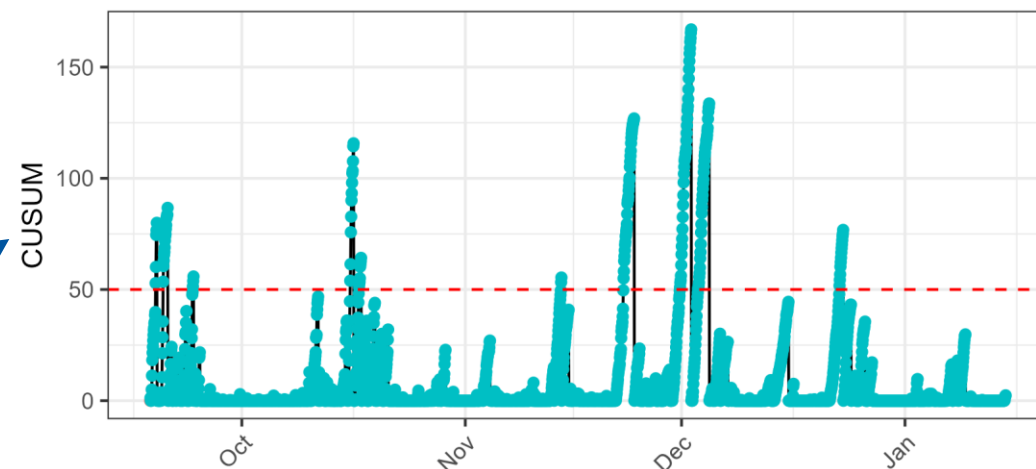


Parameter 1:

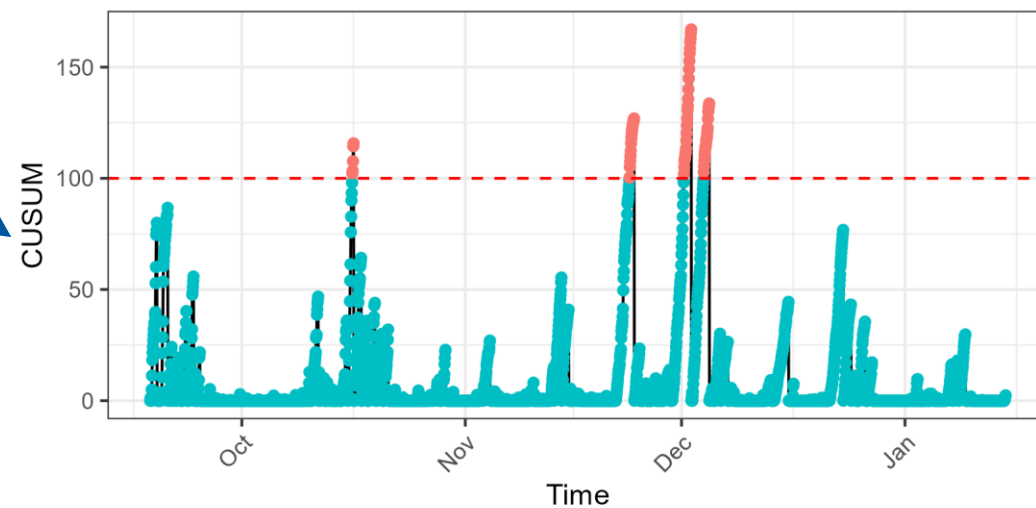
Time

Requirement
initially 12 hours,
changed to 72
hours

Cumulative sum of time series with higher K_t



Cumulative sum of time series with higher θ



Parameter 2:

CUSUM

Threshold
initially 50,
changed to 100

CUSUM vs Fixed Threshold

CUSUM

- Considers and automatically adjusts to individual user history → large variability in personal preferences
- Can alert more quickly if the time threshold is small enough
- Can identify small anomalies below the fixed threshold
- Can identify a broader range of anomalous consumption patterns
- Less intuitive for adjusting thresholds and requires more operator inputs

Fixed consumption and time threshold

- Intuitive to change thresholds
- Requires fewer operator-chosen inputs
- May require different thresholds for different meter sizes
- Could miss smaller anomalies below the consumption threshold

Both methods

- Can enhance system safety and support customers
- Can be adjusted to the operator's desired sensitivity

Prototype Communication Dashboard (Phase 2)

Select Date:

Run

Select User ID:

Ability to select new day's data and run for one day at a time

Summary of data analyzed and table of users who triggered an alert

Summary

Users

Users Analyzed and Alerts Triggered:

Total number of users analyzed: 10

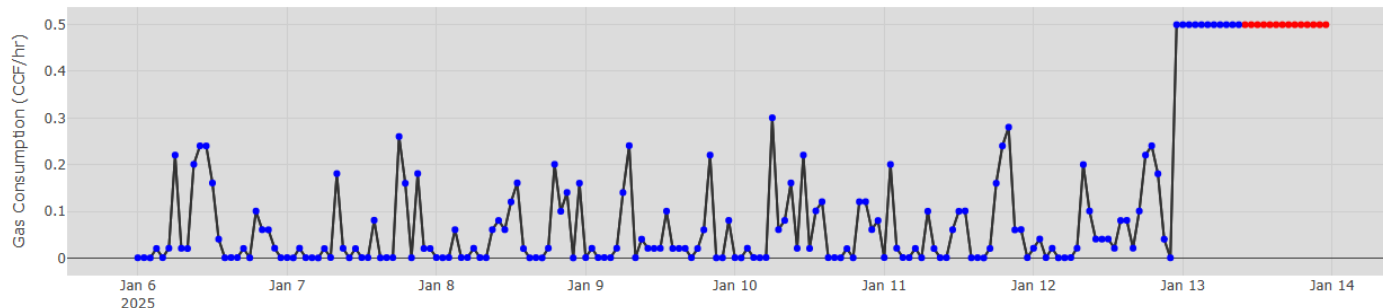
Count of consumers that had no or incomplete data: 5

Number of users who had an anomalous reading flagged in the last 24 hours: 3

Show 5 entries

Search:

Ranking	User ID	Severity	Consecutive Days with Alerts	Meter Size	Occupied Residence
1	3204747	High (698x Larger)	1	250	Yes
2	2976687	High (301x Larger)	2	250	Yes
3	3168948	Medium (81x Larger)	2	250	Yes



Opportunities for Improvement (Phase 2)

- Meter size
- Vacant vs occupied: couple with electric usage?
- Incorporating weather data
- Appliance information → integration with satellite imagery (swimming pools, NG generators)
- Training algorithms using field technician survey results (e.g., machine learning)





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Thank You!

Any Questions?

Interested in Collaborating?

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