Lawrence Berkeley National Laboratory
Environmental Energy Technologies Division Behavior Analytics
Providing insights that enable evidence-based, data-driven decisions

Load Shape Clustering of Residential Smart Meter Data

Ling Jin, Sam Borgeson, Dan Fredman, Liesel Hans, Sid Patel, Anna Spurlock, Annika Todd

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Our solution: Behavior Analytics

- **Behavior Analytics**: combine behavioral theories with cutting-edge data science
- Interpret meter data as product of preferences and behaviors
  - How should we group household energy behaviors?
  - When do households use most of their energy? Peaks?
  - How diverse are customer load shapes?
  - Etc.

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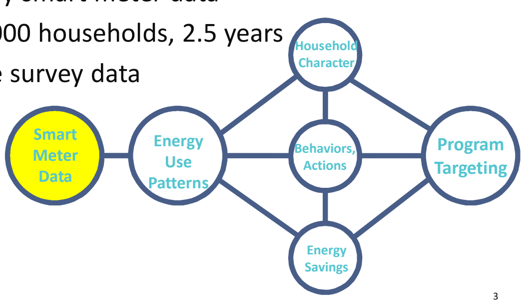
Project Overview: Data

- One utility, residential customers
- Hourly smart meter data
- 100,000 households, 2.5 years
- Some survey data



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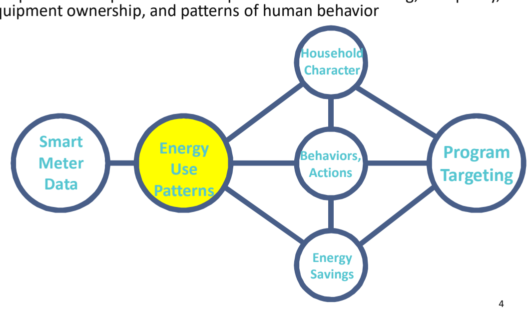
Project Overview

- Identify a finite set (aka dictionary) of representative load shapes that best describe all observed shapes
- Interpret these representative shapes in terms of scheduling, occupancy, equipment ownership, and patterns of human behavior



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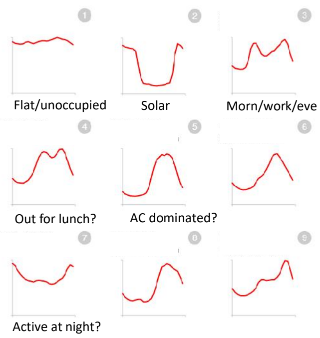
Defining Load Shapes

- A load shape is the pattern created by 24 hours of demand data.
- Shapes are produced by patterns of occupancy, equipment ownership, and behavior



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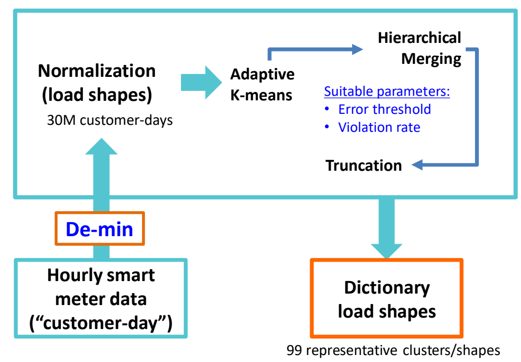
Clustering approach



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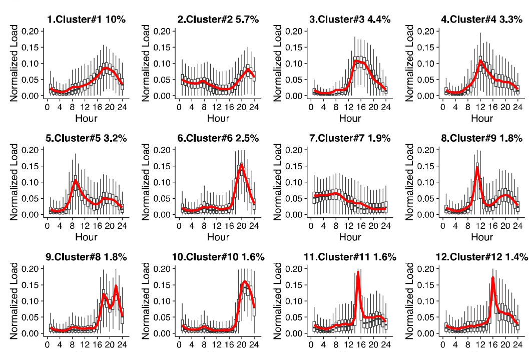
Top 12 Clusters



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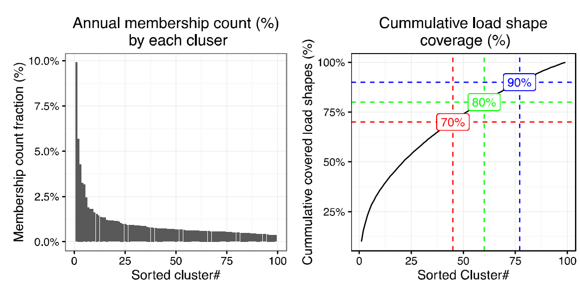
Cluster coverage



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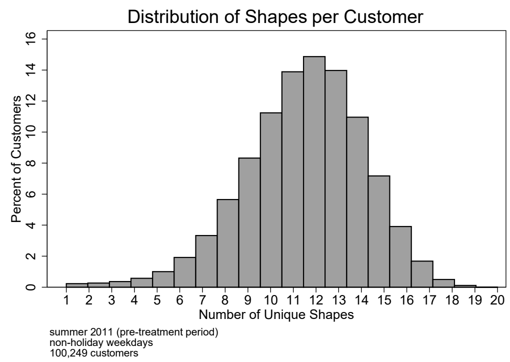
Can we create customer groups?



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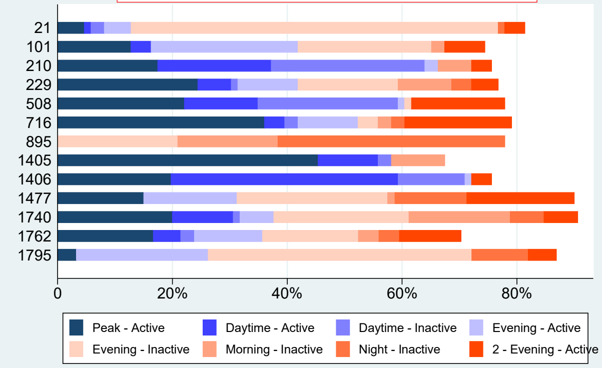
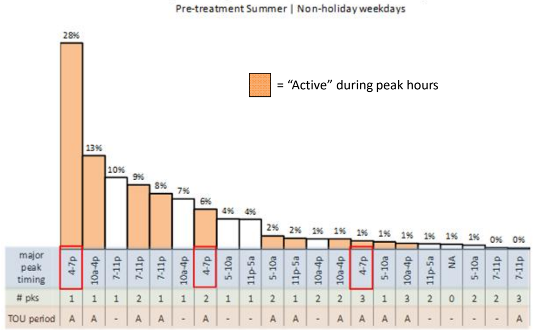
Energy "personalities"



Breakdown of shape characteristics

Shape-Groups: Percent of all Customer-Days
Pre-treatment Summer | Non-holiday weekdays



major peak timing	4-7p	10a-4p	7-11p	7-11p	7-11p	10a-4p	4-7p	5-10a	11p-5a	5-10a	11p-5a	10a-4p	10a-4p	4-7p	5-10a	10a-4p	11p-5a	NA	5-10a	7-11p	7-11p
# pks	1	1	1	2	1	1	2	1	1	2	1	2	2	3	1	3	2	0	2	2	3
TOU period	A	A	-	A	A	-	A	-	-	A	A	-	A	A	A	A	-	-	-	-	A

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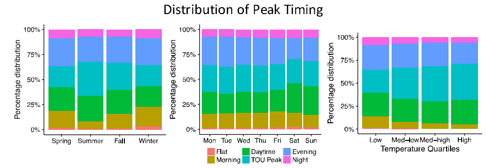
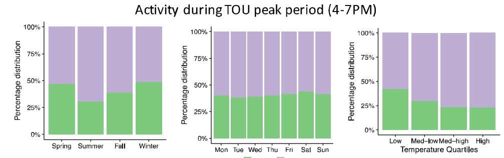
Peak timing and magnitude

Distribution of Peak Timing



Activity during TOU peak period (4-7PM)



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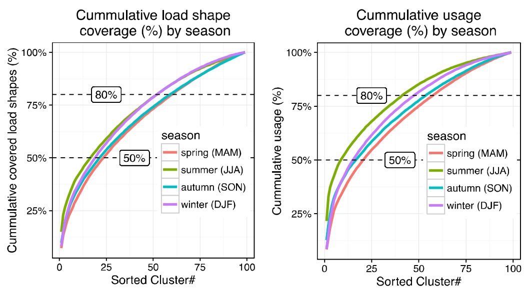
Seasonal load shape diversity



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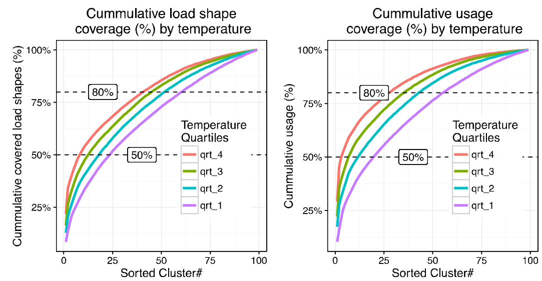
Temperature driven load shape diversity



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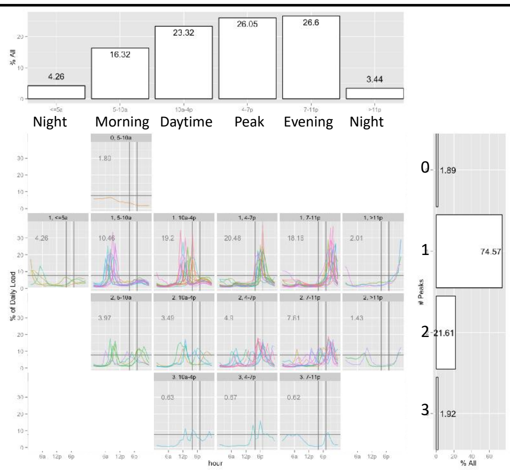
Contact:
Sam Borgeson
sam@convergenceda.com

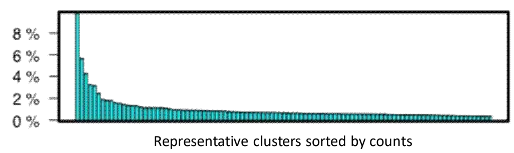
Ling Jin
ljin@lbl.gov



Clustering Results

- Applied clustering to pre-treatment year:
  - ~ 10^5 customers, ~$3\text{x}10^7$ load shapes (customer-days)
- 99 representative clusters/shapes
  - 30% violation rate to error threshold 0.3.

% of shapes by count for each representative clusters



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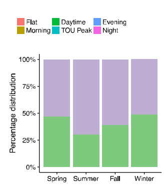

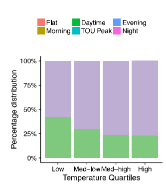

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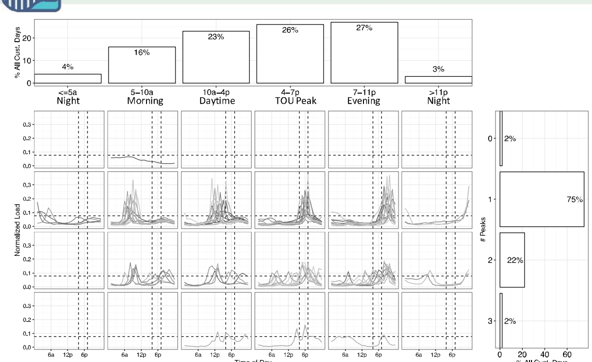
99 Load Shape Clusters



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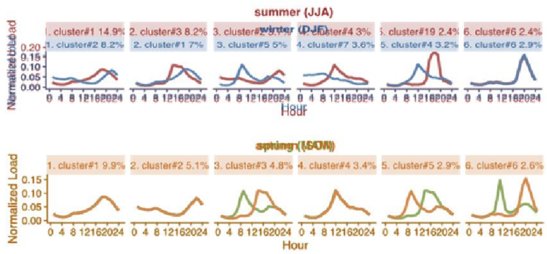
Top 6 shapes by season



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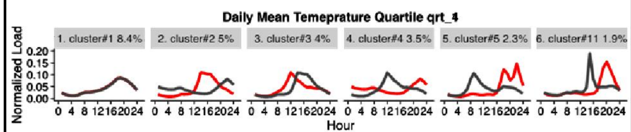

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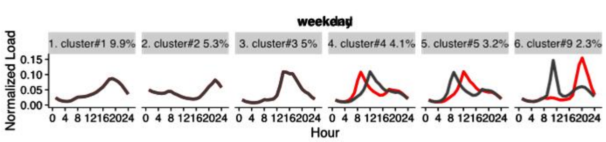
Weekday vs. Weekend



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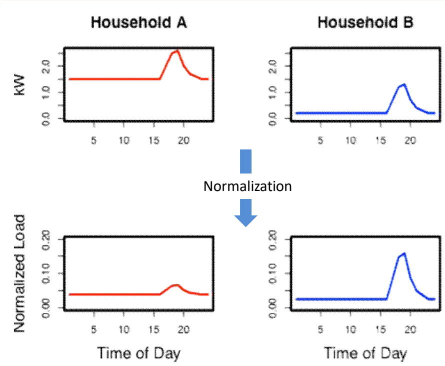
Normalization Flattens Load Shapes



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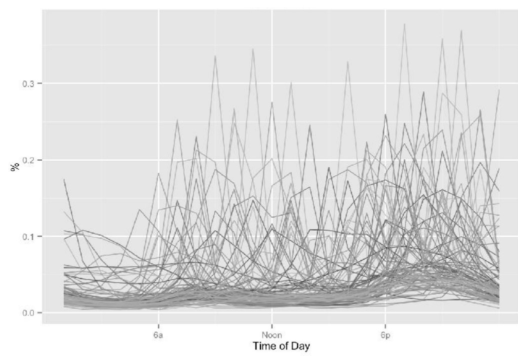
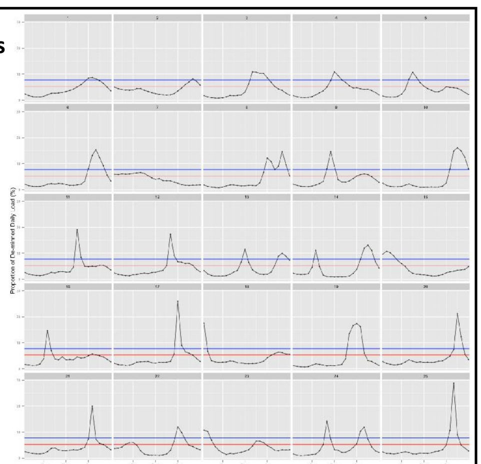
99 Load Shapes: Now What?

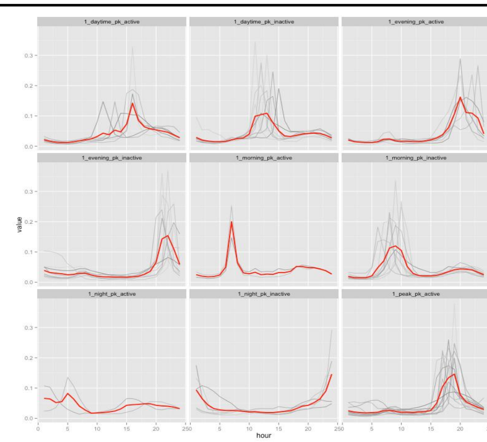


99 Load Shapes: Now What?

- Distill 99 into more usable groupings
  - → How should they be grouped?
- Behavioral dimensions in TOU context:
  - Number of peaks
  - Timing of peaks
  - Activity level during TOU period
- Can we blend qualitative intuition with data-driven processes?

1. Find breaks in data





Can we create customer groups?

Examples:

- "Consistent" HHs = customers with only 1 or 2 shapes over all summer, non-holiday weekdays
  - Typically HHs with only 1 or 2 adults in the home
- What increases variation in a customer's number of shape-groups?
  - Kids
  - Electric Dryer

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Next Steps

- How to assign a household to a group?
  - How different are the groups?
  - How consistent (i.e., reliable) are HHs?
    - => Further consolidation of shapes
- Are there any useful patterns via survey responses?
- How much does weather matter?
  - What is the distribution of shapes on event-like days?
- Are there patterns by day of week?

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