



Data-Driven Management for a Sustainable Energy Grid

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BECC, Sacramento
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Work with Ram Rajagopal, James
Sweeney, June Flora, and Sam
Borgeson



Outline

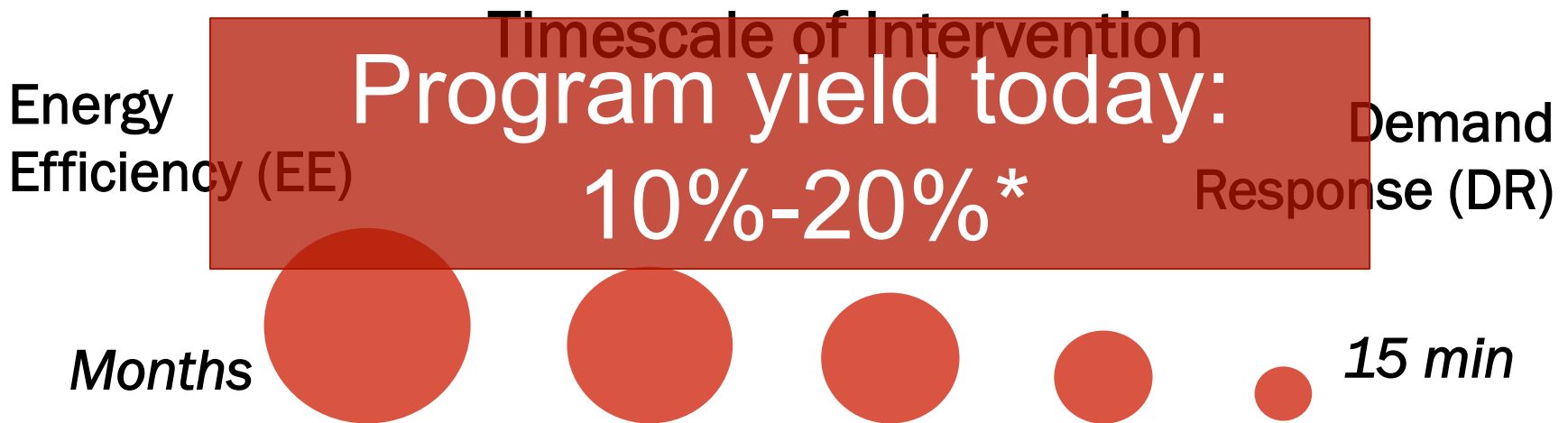
- **Context: Energy Program Targeting**
- A Structural Temperature Response Model
- Applications



Energy Program Targeting

Problem:

Identify, engage and incentivize willing and responsive users to improve consumption behavior

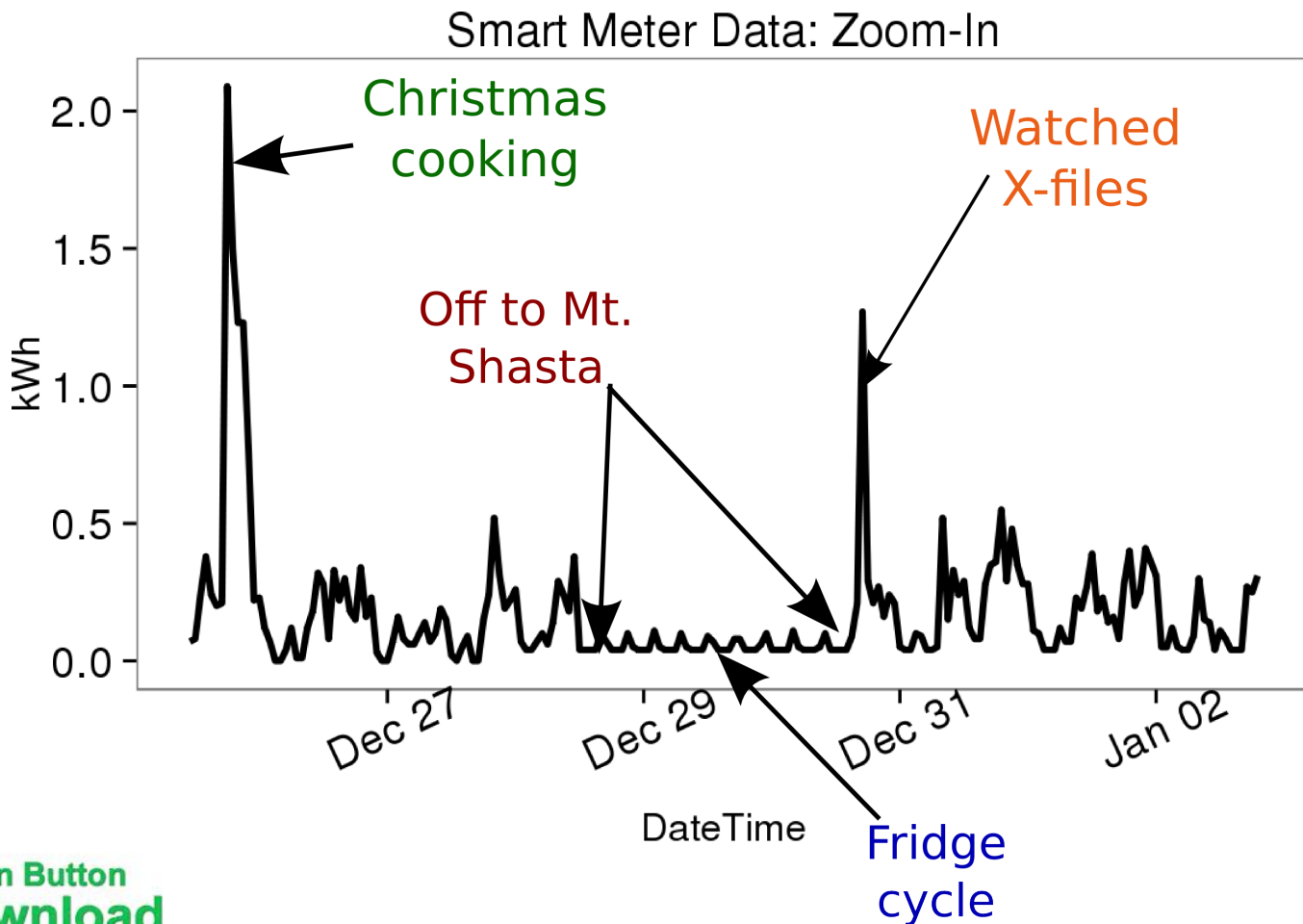


$$\text{yield} = \frac{\text{Achieved Reductions}}{\text{Potential Reductions}}$$

(*ACEEE, 2011)



Understanding Consumption

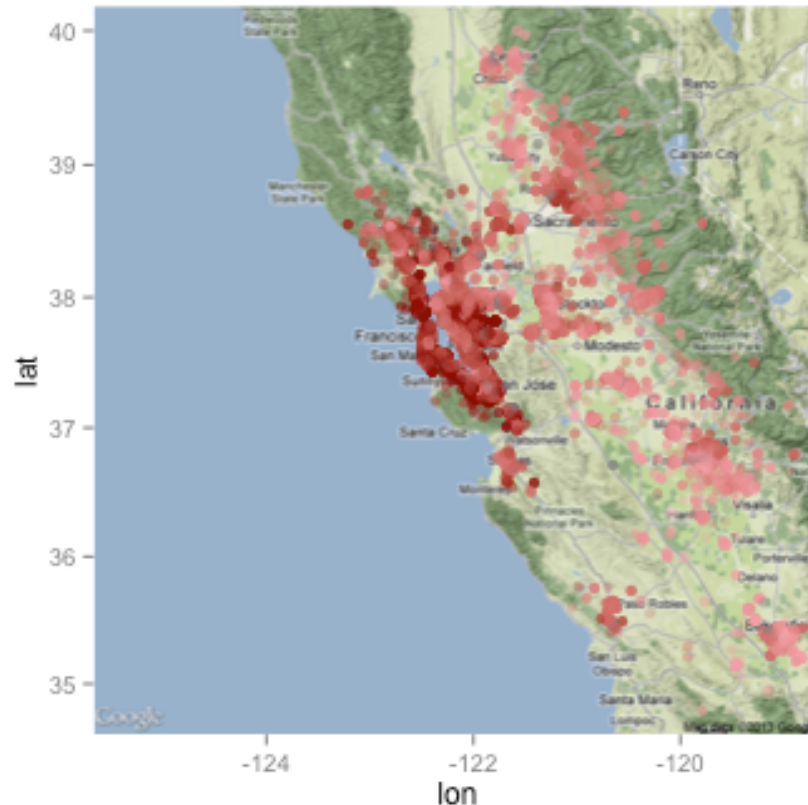


Green Button
Download
My Data[®]



Data Snapshot: Time Series

- **Consumption:**
 - PG&E: 120,000 CA users, 43M days, hourly
 - Google: 1000 US users (trial experiment)
- **Weather:** scraped off www.wunderground.com





Google Questionnaire

Appliance Questions	% Yes
Have clothes dryers?	63%
Has more than 1 fridge?	26%
Has spa, hot tub, or pool?	8%
Has washing machine?	92%
Has more than one computer?	95%
Has plasma TV?	26%

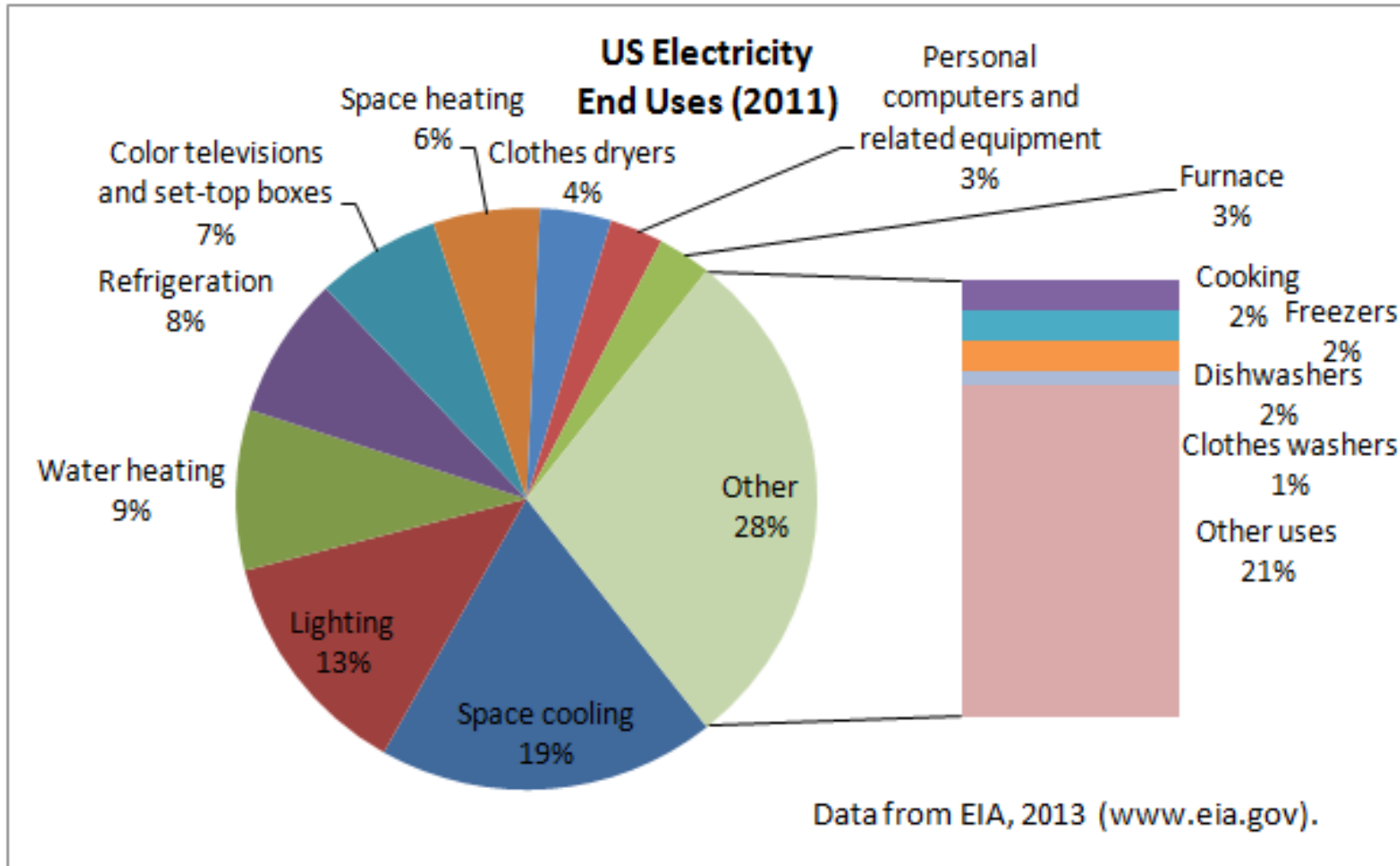
Lifestyle/Occupancy	% Yes
Do children under 5 live in household?	33%
Do non-employed people live in household?	30%
Do elderly people live in household?	2%
Do you work from home?	18%

+100 more questions on appliances, lifestyle, attitudes toward energy use...



Thermal Electricity Demand

HVAC (Heating + Cooling) = 25% of total electricity use





Outline

- Context: Energy Program Targeting
- **A Structural Temperature Response Model**
- Applications

Albert, A., Rajagopal, R. Thermal profiling of residential energy consumers. *Review and Resubmit, IEEE Transactions on Power Systems, 2013.*



The “Nest” Targeting Problem



Whom to offer
Nest thermostat
rebates to?

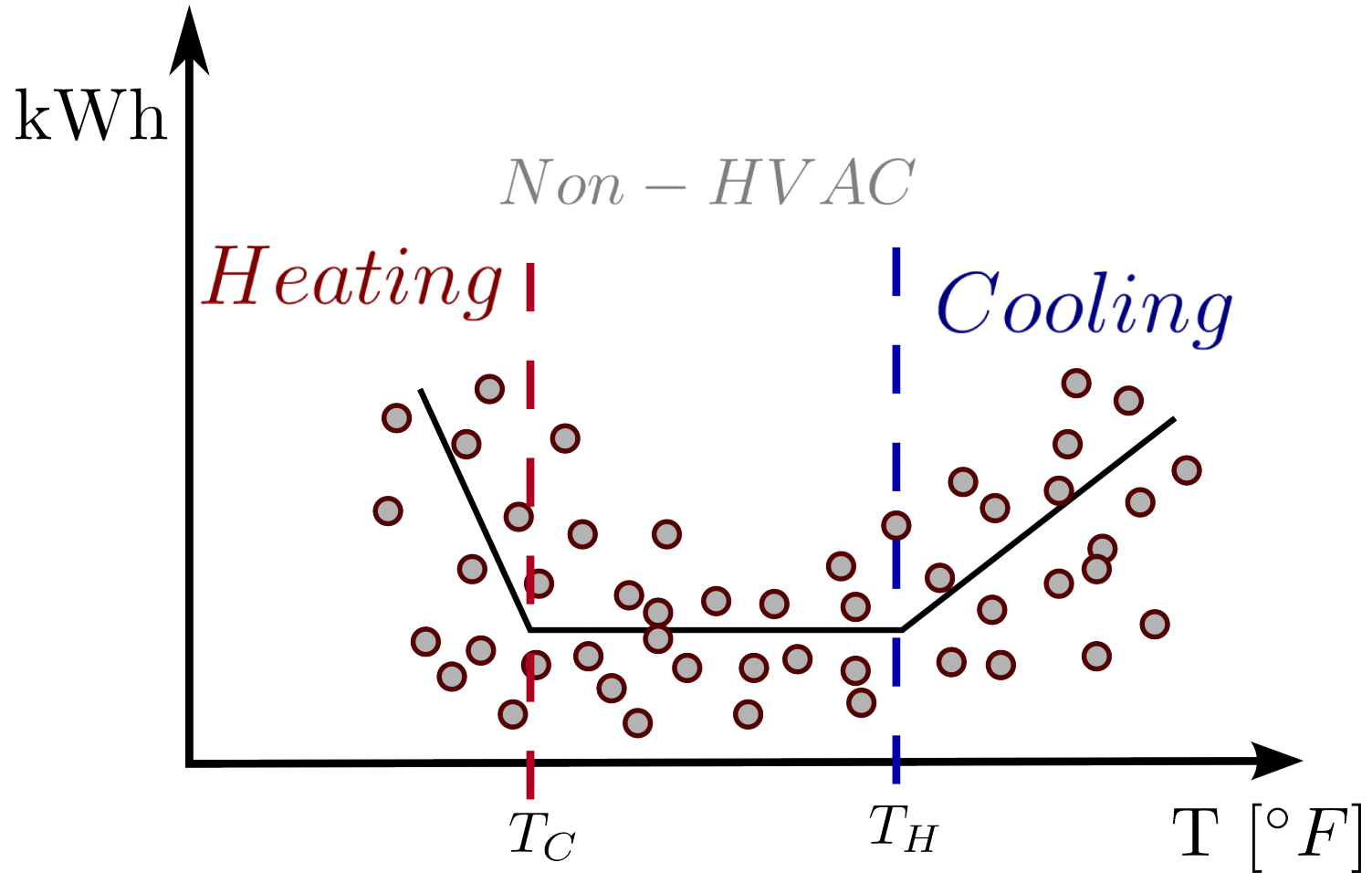
$$\Delta E = 1^{\circ}F \times \frac{dE}{dT} \left[\frac{\text{kWh}}{^{\circ}F} \right]$$

Consumption Averted Temperature Setpoint Change Consumption Response Rate

- Occupancy, lifestyle, building thermal mass...



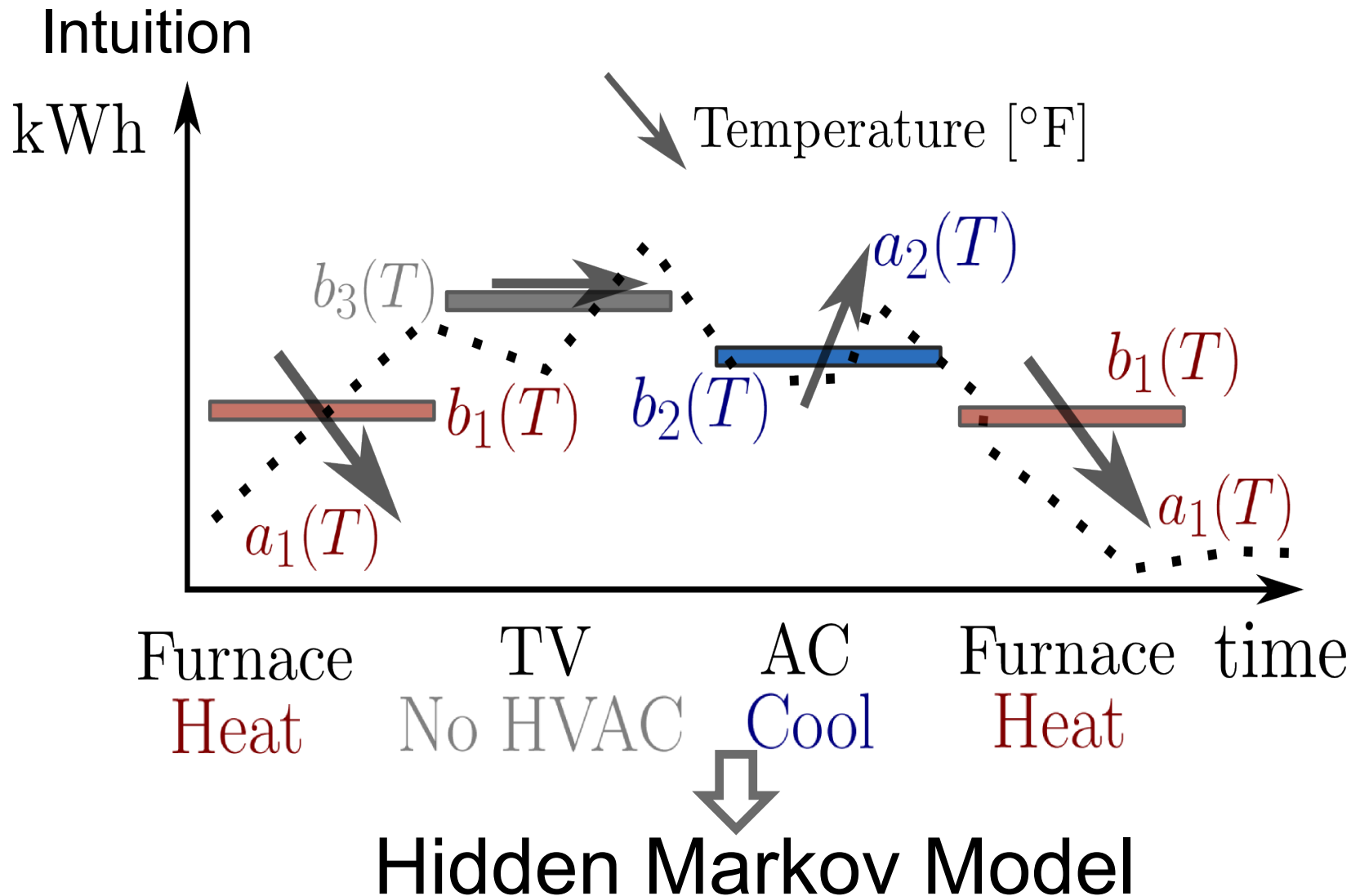
Structuring Thermal Consumption



- Behavioral response model to identify the right users



Thermally-Sensitive Occupancy States

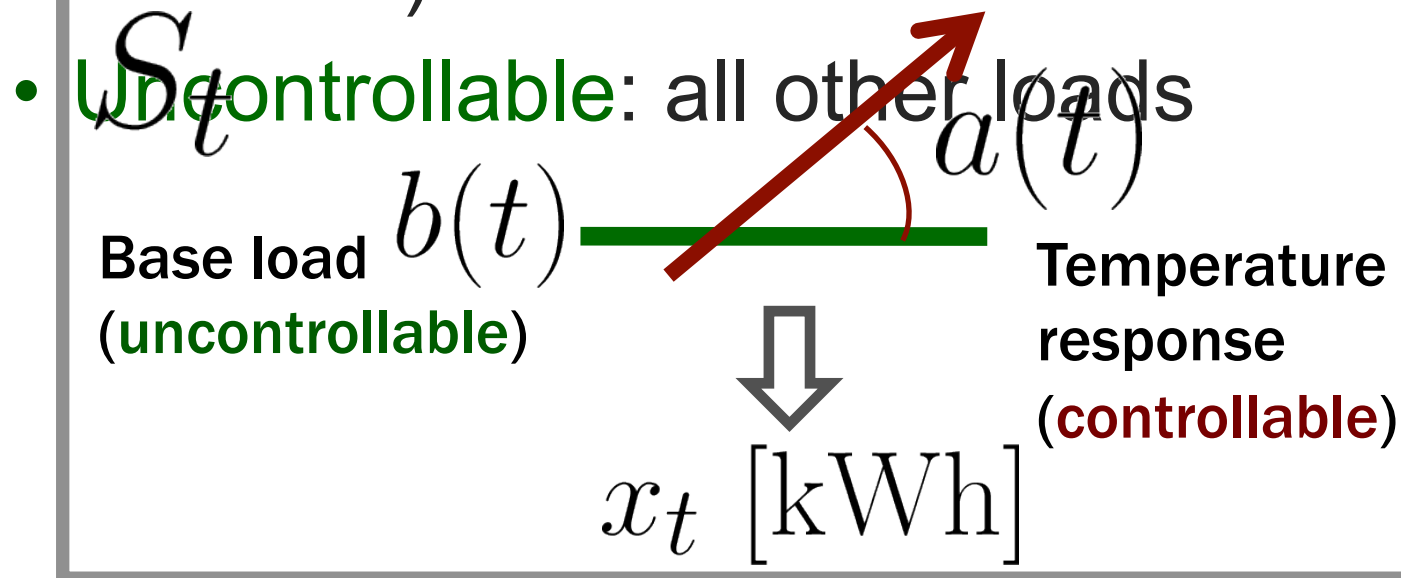




Coarse Thermal Disaggregation

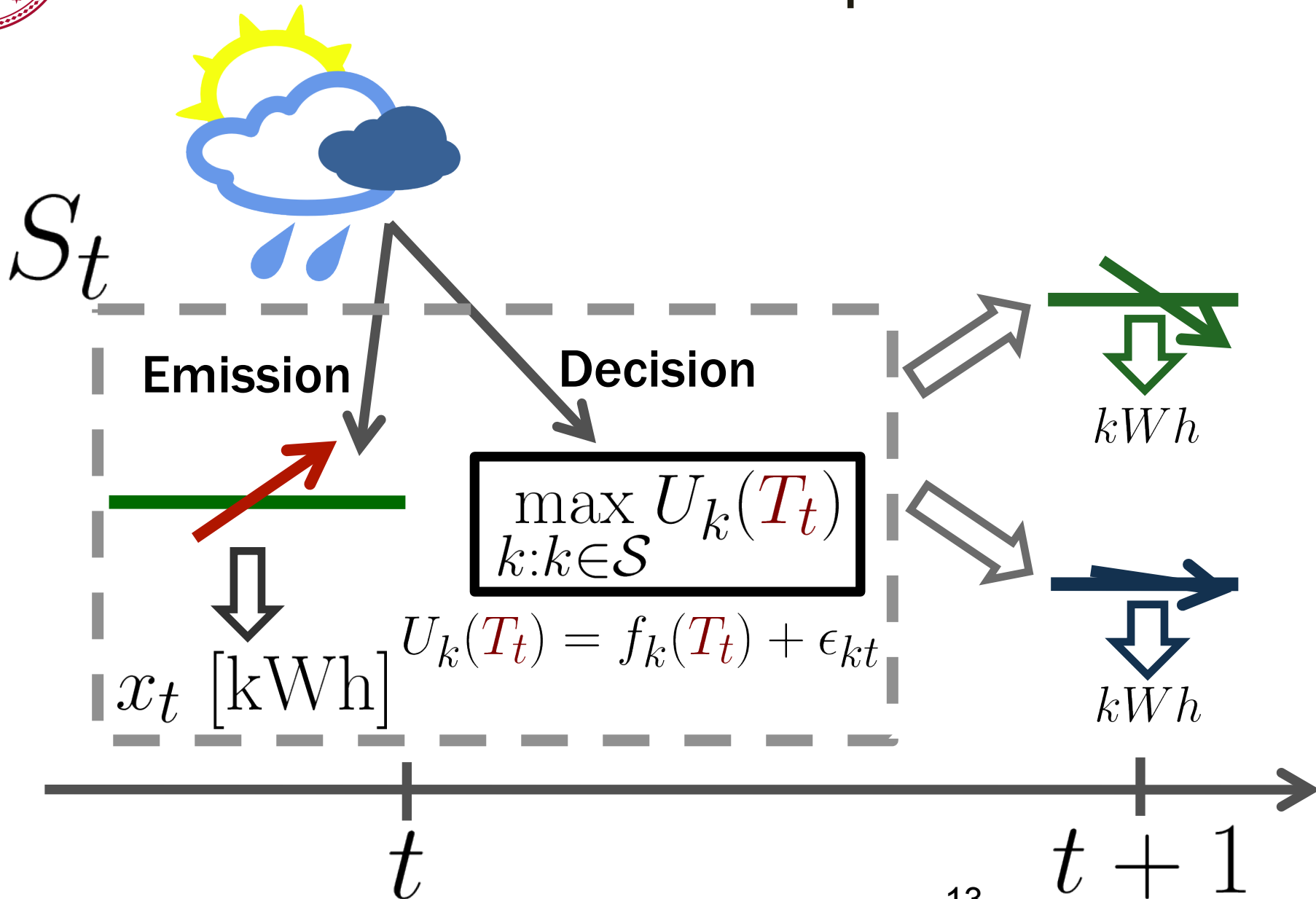
- Decompose consumption into two parts:

- Controllable:** HVAC (temperature-sensitive)



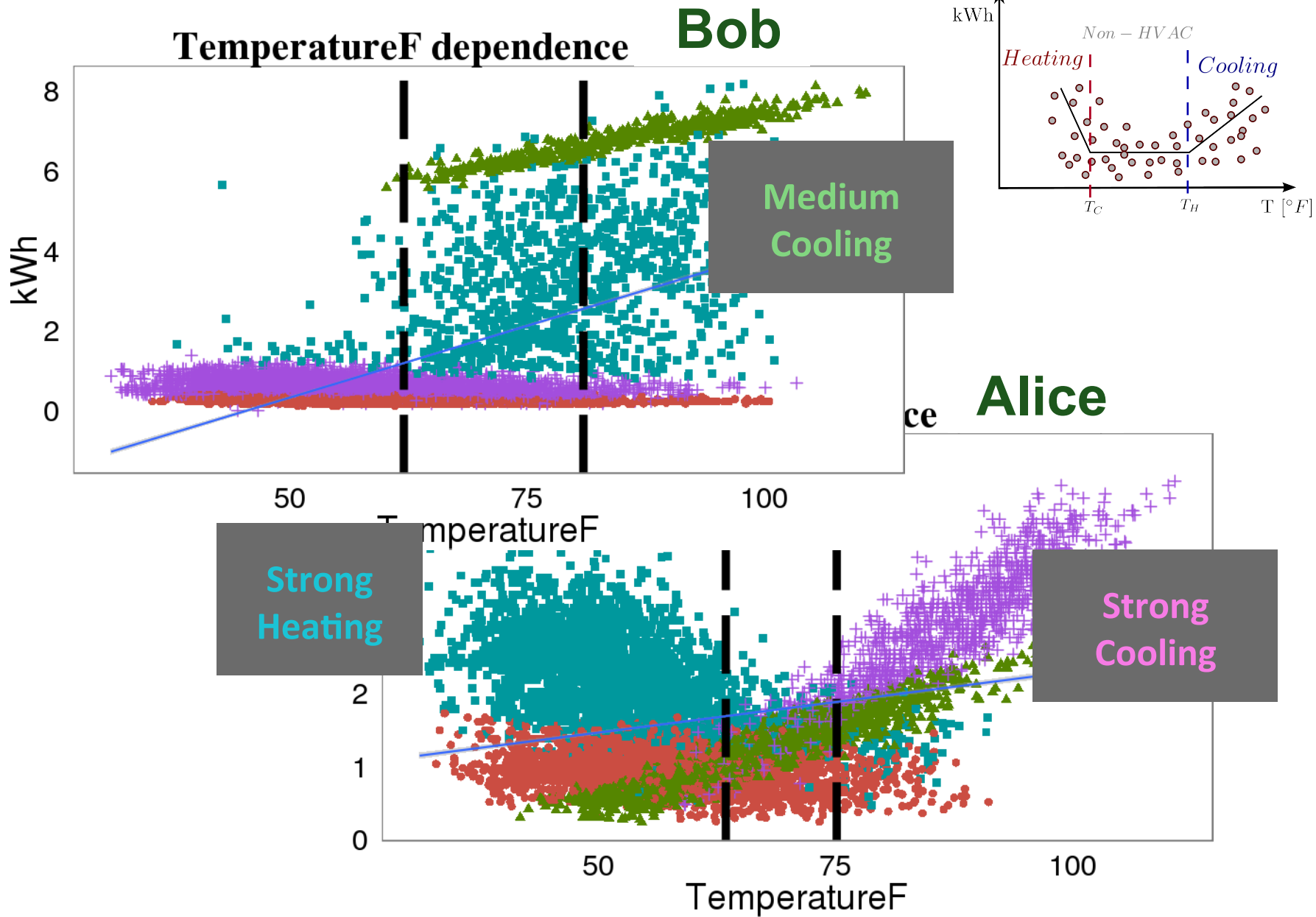


A Structural Thermal Response Model



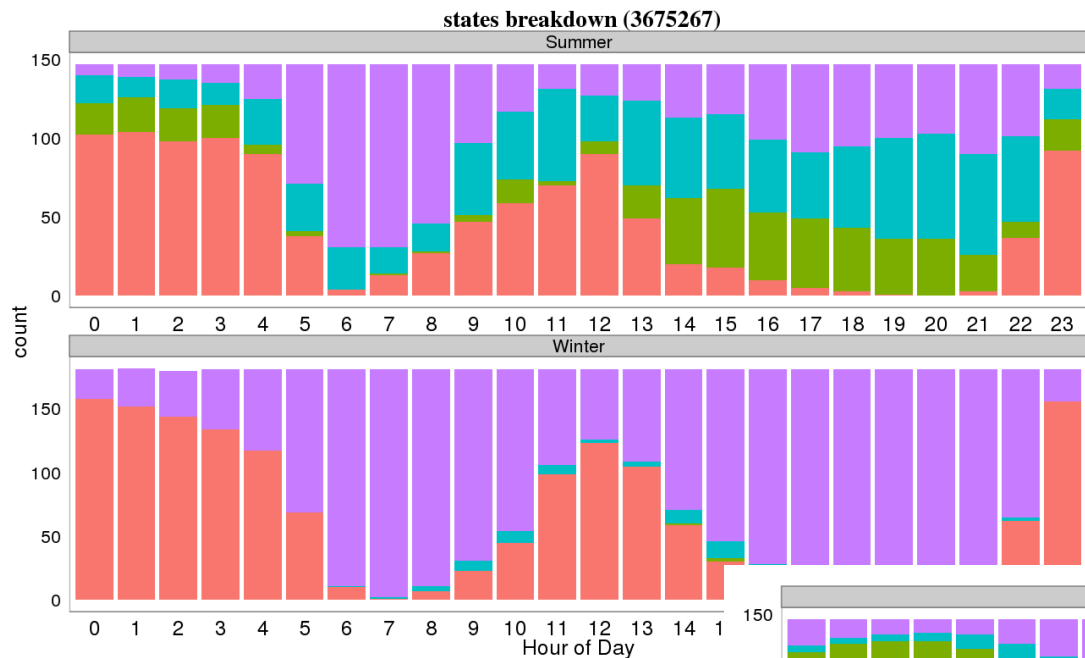


Alice and Bob

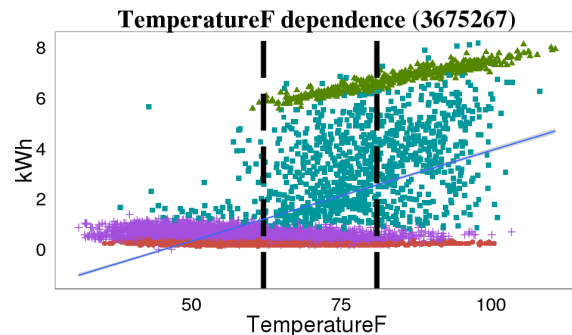




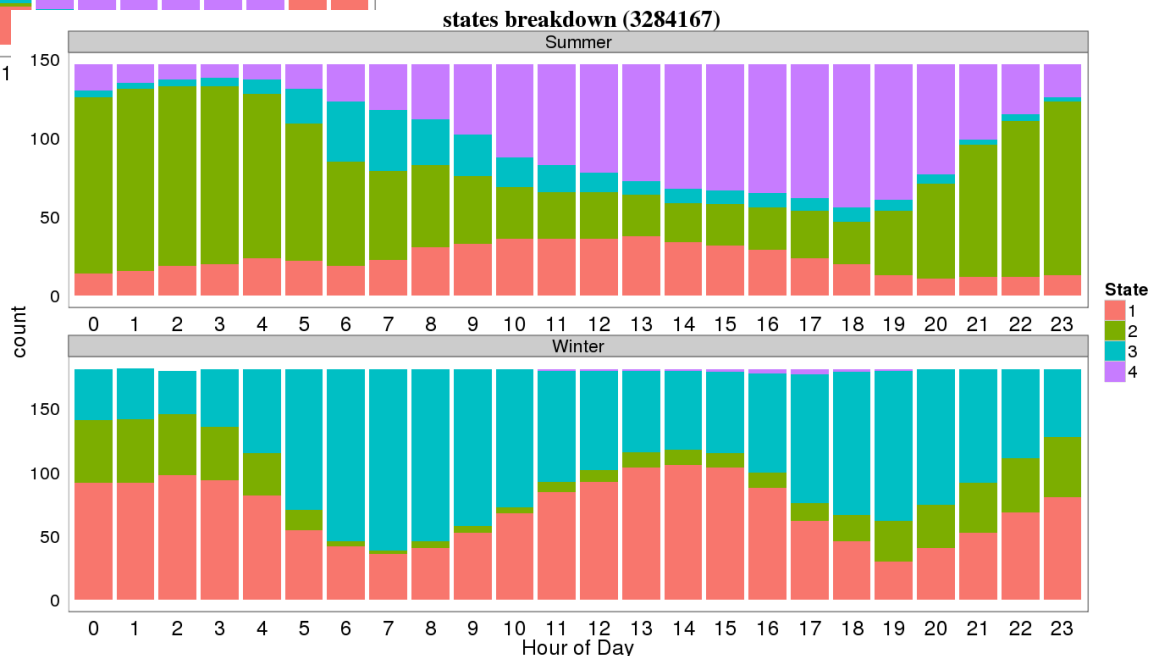
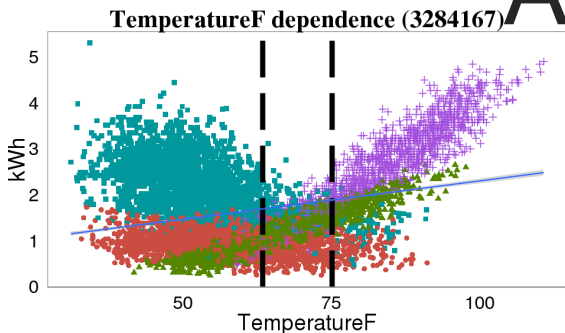
Seasonal and Daily Profiles



Bob



Alice

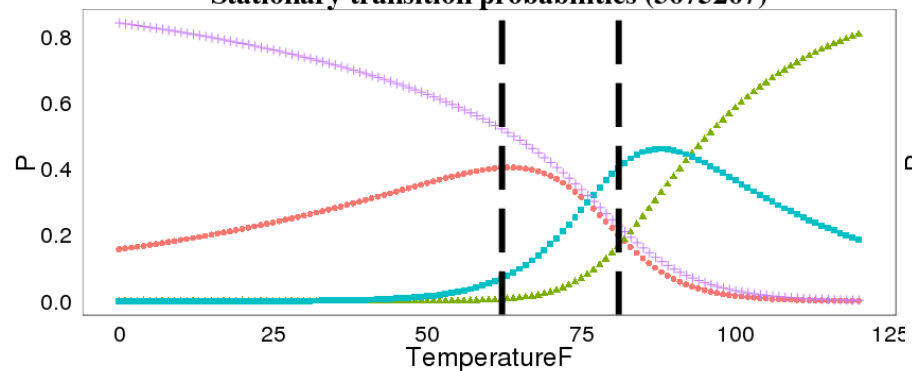




Effective Thermal Sensitivity

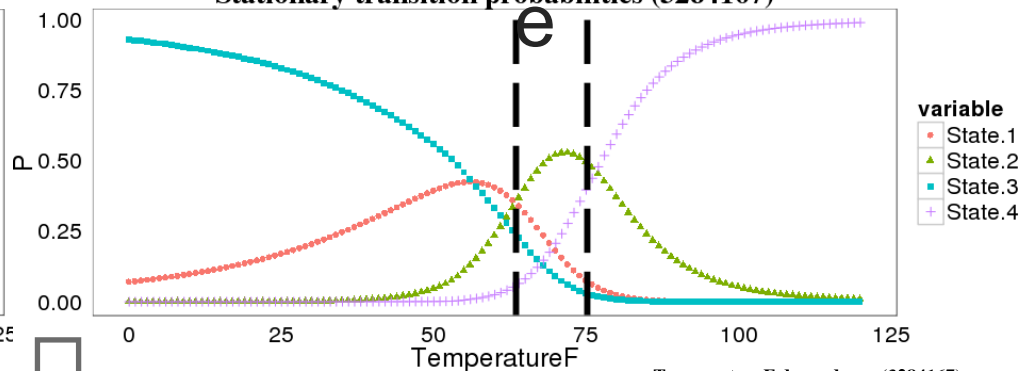
Bob

Stationary transition probabilities (3675267)



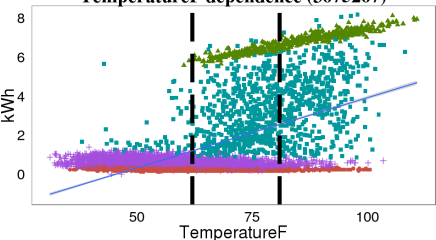
Alic

Stationary transition probabilities (3284167)

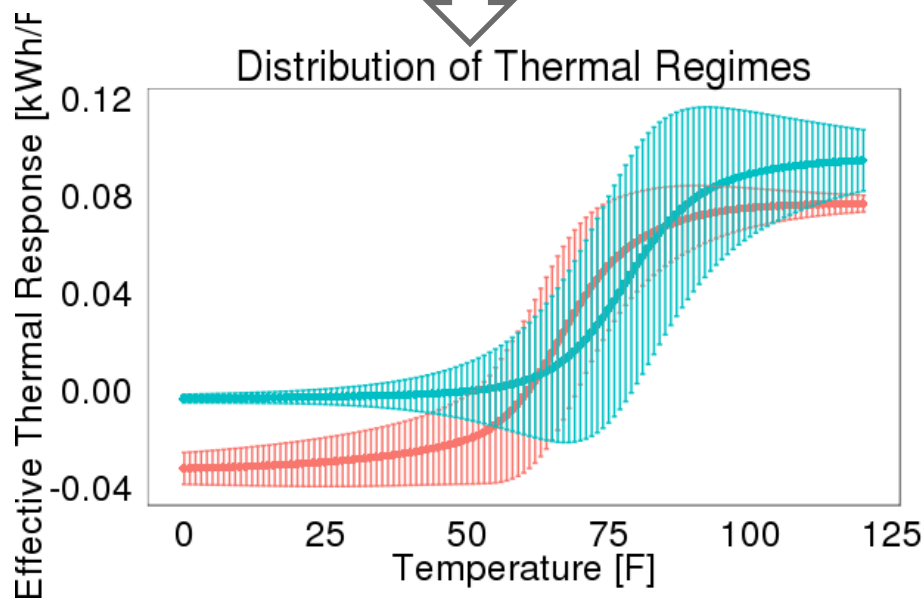


variable
State.1
State.2
State.3
State.4

TemperatureF dependence (3675267)

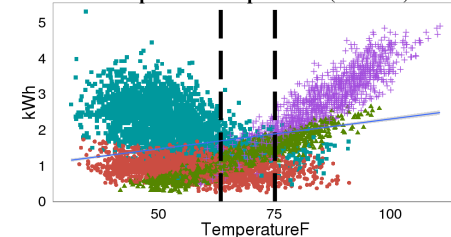


Distribution of Thermal Regimes



Alice
Bob

TemperatureF dependence (3284167)





Outline

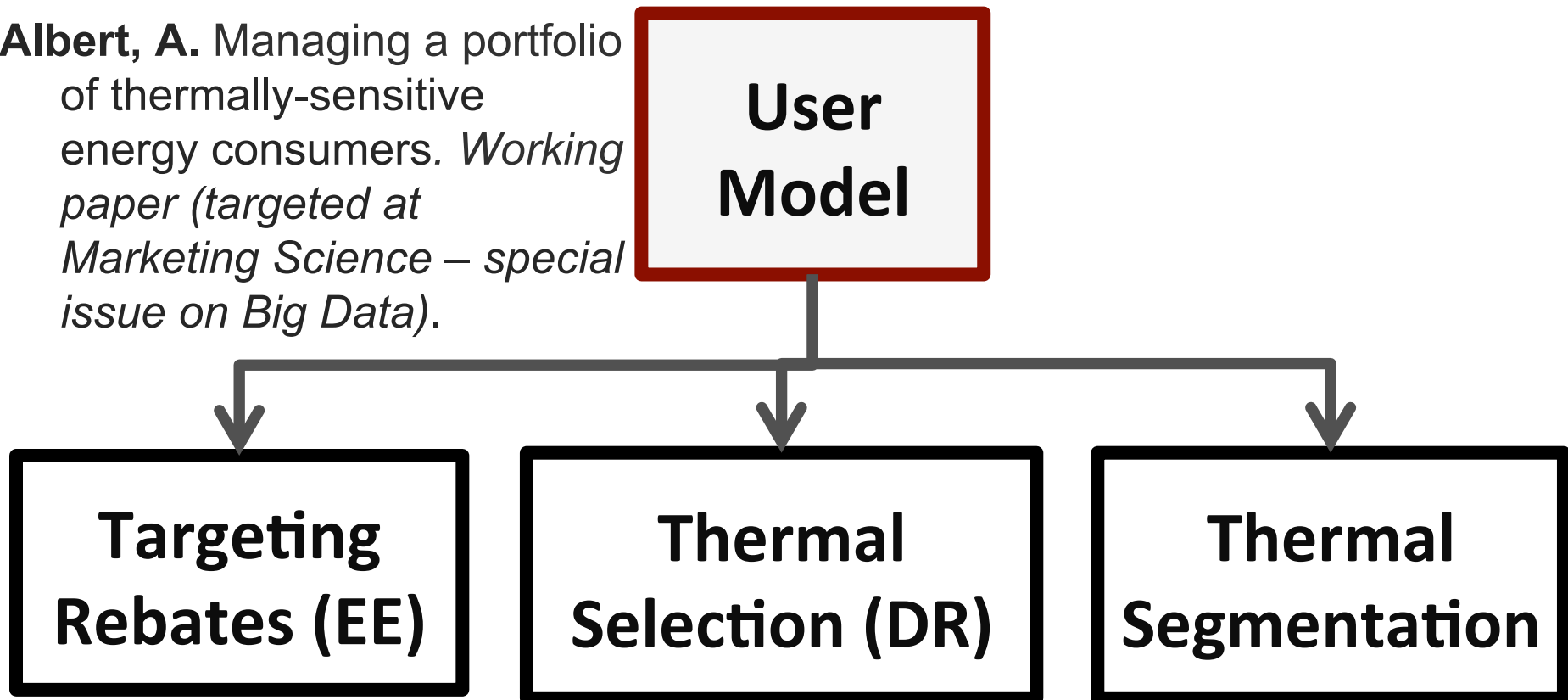
- Context: Energy Program Targeting
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Applications

So we have response models. Now what?

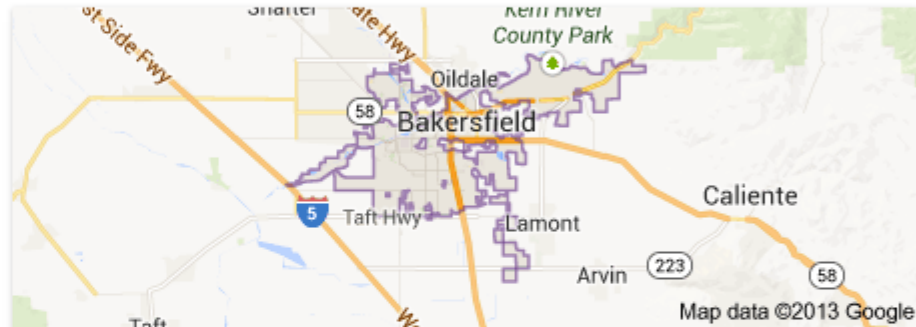
Albert, A. Managing a portfolio of thermally-sensitive energy consumers. *Working paper (targeted at Marketing Science – special issue on Big Data).*





Bakersfield, CA

- ~2000 users , 1 year of data, hourly readings
- **Hot**, arid climate: predominant AC



Bakersfield

City in California

Bakersfield is a city near the southern end Kern County, California. It is roughly equidistant to Los Angeles, which are 110 miles to the north

[Wikipedia](#)

Area: 143.6 sq miles (371.9 km²)

Weather: 60°F (16°C), Wind W at 0 mph

Population: 358,597 (2012)

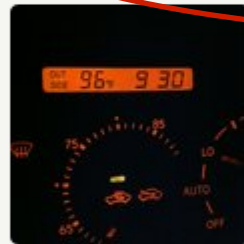


👍 158
★ 17

Drey T.
Hungry Valley, CA

★ ★ ★ ★ ★ 6/12/12

I don't know how anyone lives in this city! I drove through it at 9:30pm and it was 96 degrees! Lawd have mercy! I would have hung myself by now!



Good lord!

Was this review ... ?

💡 Useful 5

😄 Funny 10

❄️ Cool 2



Simple “Nest Targeting”

Identify user subset that are most sensitive to cooling

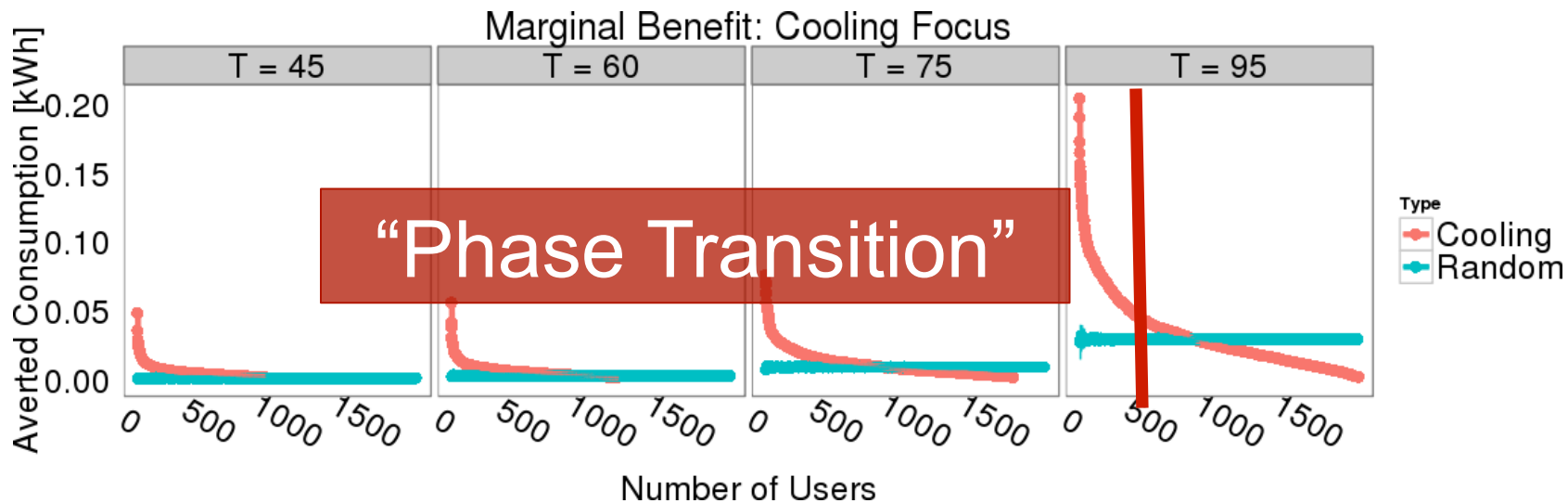
$$\begin{aligned} & \max_{\mathbf{x}} \mathbb{E} \left[\sum_i x_i \beta_1(T) \right] \\ & s.t. \sum_i x_i = N \\ & \quad x_i \in \{0, 1\} \end{aligned}$$





Simple “Nest Targeting”

Identify user subset that are most sensitive to cooling

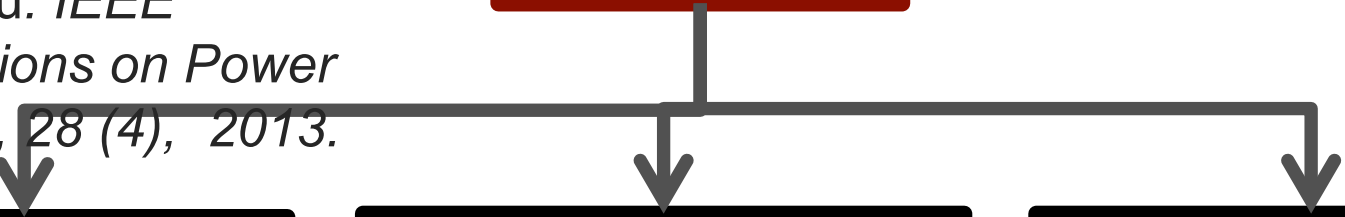
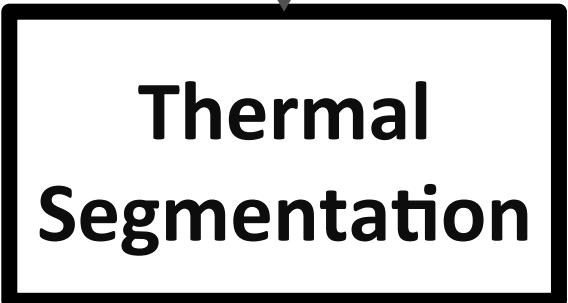
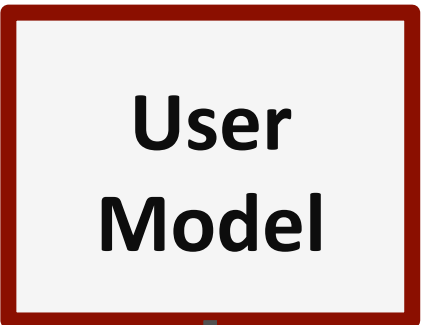




Applications

So we have response models. Now what?

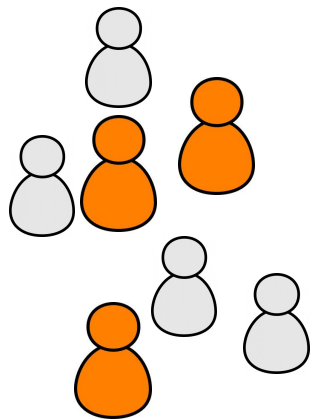
Albert, A., Rajagopal, R. Smart meter driven segmentation: what your consumption says about you. *IEEE Transactions on Power Systems*, 28 (4), 2013.





Learning about the User

Old way: programs at utilities generally use questionnaires to perform “psychographic” market segmentation



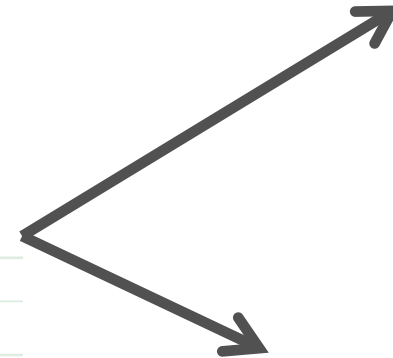
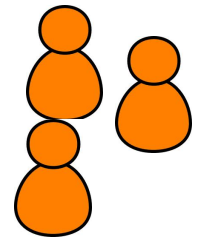
Over the past three months, how often have you or your household members done the following? *

Use the not relevant category when the appliance indicated is in an area that serves more than one household or if you or no one in your household does performs the behavior listed

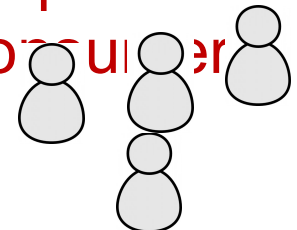


	Not relevant	Rarely (less than 25% of the time)	Occasionally (25% - 50%)	Often (50% - 75%)	Almost always (more than 75% of the time)
Turn off computers when not in use	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Turn off the TV when you were the last person to leave a room	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Turn off gaming and entertainment devices such as, Xbox and DVD players when you were the last person to leave a room	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

“Green enthusiasts”



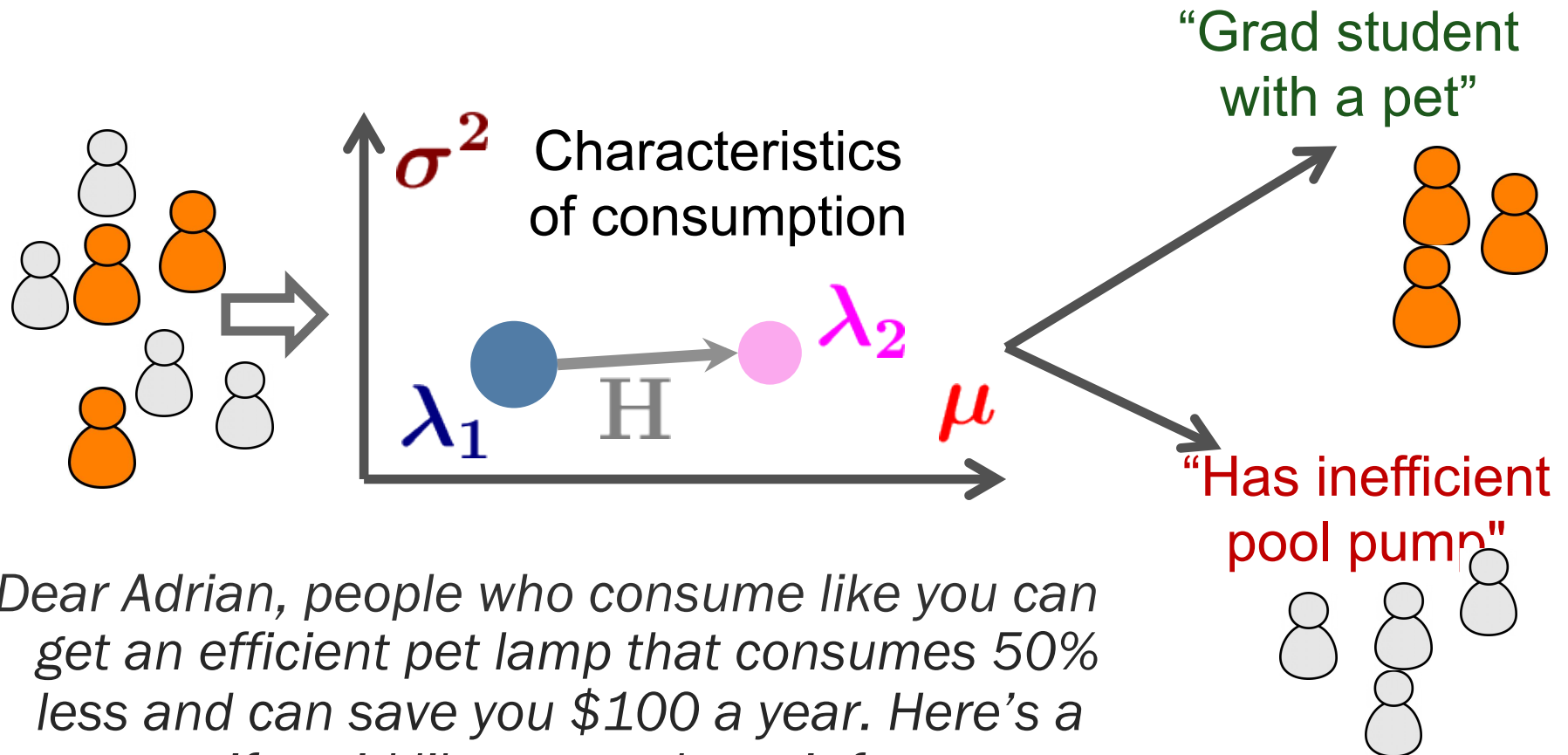
“Apathetic
COMPUTER USER”





Learning about the User

New way: actually use the data to make lifestyle inferences: Classification



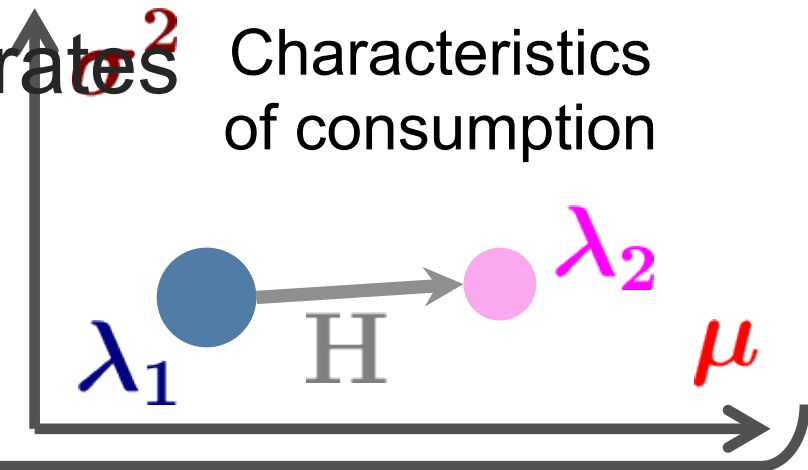
"Dear Adrian, people who consume like you can get an efficient pet lamp that consumes 50% less and can save you \$100 a year. Here's a coupon if you'd like to purchase it from our preferred partners."



Consumption Features

$$\text{kWh} = f(\text{Occupancy Patterns}, \text{Weather})$$

- **Magnitude** – base loads, rates
- **Duration** – typical duration
- **Variability** – entropy



Classifier

AdaBoost
[Freund &
Schapire, 1996]

User
Characteristics



Performance vs Random Guessing

Are consumption characteristics informative of user attributes?

Question	Improvement over random guessing*
Clothes Dryers	19%
Washing Machines	19%
Central AC Units	17%
Individual Under 5 (Infants)	11%
Unemployed Residents	10%
Work from home	7%

*5-fold cross-validation out-of-sample results
Accounting for empirical distributions in the



User and Consumption Characteristics

- **Appliances:** state **base loads** and **variances**
 - variance: indication of occupant activity
 - washing machines
 - hot tubs/spas...
- **Lifestyle:** state variability
 - small children (under 5)
 - unemployed members of household



Thank You!

“Half the money I spend on advertising is wasted; the trouble is I don’t know which half.”

John Wanamaker, Philadelphia, PA.

Now we have data to tell which half.