How to Use Python and Mathematical Modeling to Better Understand the Impact of Electricity Pricing on Consumption

Saba Nejad

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PyData NYC 2023

Hi! I'm Saba. Thank you for coming to my talk.

My name is Saba. I'm a Data Engineer at Point72. Today, I'll be walking you through part of my master's thesis that I worked on and defended two years ago at MIT.

Goals for this talk

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  - how it was collected
  - its biases
  - dimenstionality, fill-rate, etc.

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- Before trying to fit a model to your data, you should have a mathematical model rooted in the real world.

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- the thinking behind the mathematical framing of the problem.
- the analysis based on the particular dataset and mathematical model.
- results, takeaways, lessons learned.

Useful Details about the Problem Space

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- As a result, **supply must meet demand** at all times.
- If demand exceeds supply, there will be a power outage.
- Power outages are extremely costly and we try to prevent them as much as possible.

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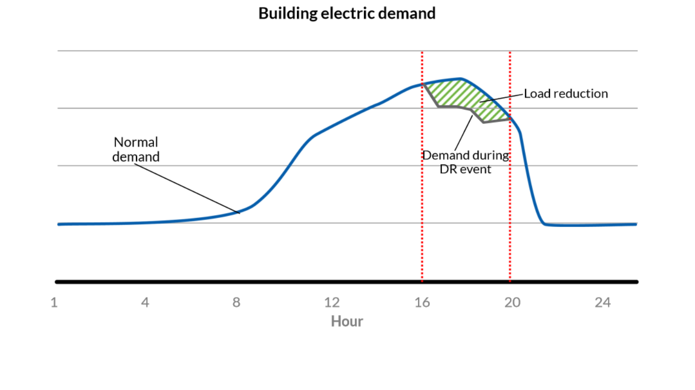
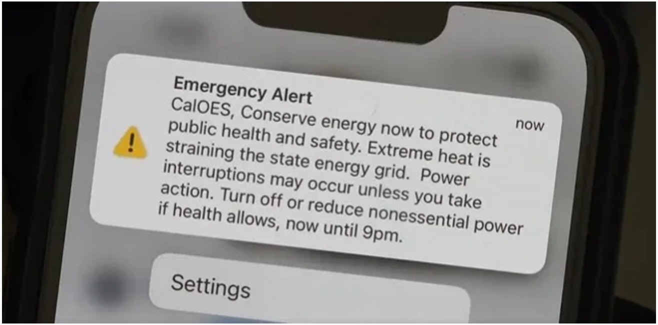
- This unique feature of electricity, poses a **challenge**.
- Imagine an unpredictably hot day where there is more demand than expected.
- To prevent a power outage, we need close to real-time methods to lower demand.
- **Demand Response** is one such method.

Demand Response visual example



Demand Response is a tragedy of the commons issue.



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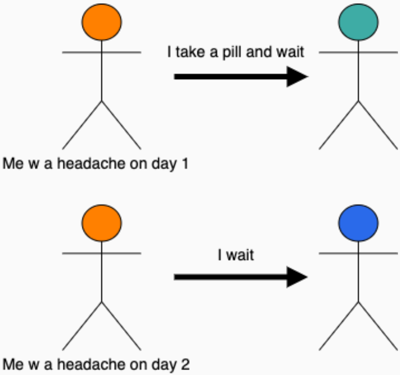
- Two pricing models:
    - Time of Use Pricing
    - Dynamic Time of Use Pricing

Repeat

There is a pricing model, called **Dynamic Time of Use Pricing**, that uses price incentives to lower demand on the grid and prevent a power outage.

Understanding causality and some useful terminology

- What does it mean for something to have a causal effect on something else



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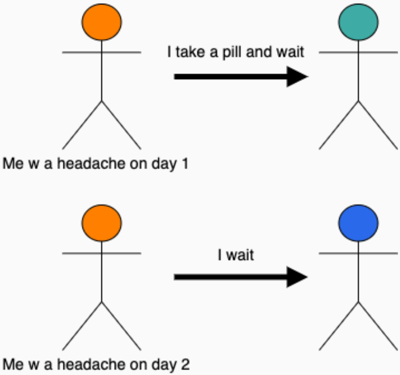

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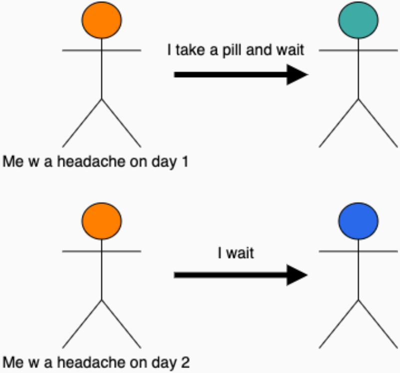
- What is a treatment
- What is the counterfactual



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- Y_0 and Y_1 are **counterfactuals** of one another. We observe **only** Y_1 or Y_0, but not both at the same time.

Solutions Around FPCI

1. Temporal Stability & Causal Transience

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Solutions Around FPCI for this Trial

1. Temporal Stability & Causal Transience X
2. Unit Homogeneity X
3. Estimate causal effects for populations rather than units ✓

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- It's difficult to estimate the treatment effect for a unit.
  $\Longrightarrow$ analyses are done on a **population vs a unit**.
- When estimating treatment effect for populations, to remove bias terms, we want samples that behave similarly out of sample.
  $\Longrightarrow$ analyses are done on **random samples** of populations.

The Details of the Trial Studied

Low Carbon London Smart Meter Trial

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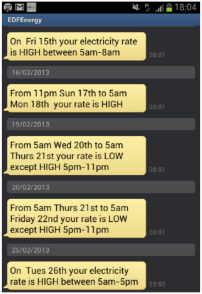
- "Dynamic": Prices were given a day ahead via the Smart Meter In Home Display or text message.



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- dTou price bands vs static pricing model:

dToU Pricing Model	Static Pricing Model
High (67.20 p/kWh)	14.228 p/kWh
Normal (11.76 p/kWh)	14.228 p/kWh
Low (3.99 p/kWh)	14.228 p/kWh

Additional Features: Discrete Socio-Economic Categories

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Label	Acorn group	Acorn category
A	Wealthy executives	Wealthy achievers
B	Affluent greys	Wealthy achievers
C	Flourishing families	Wealthy achievers
D	Prosperous professionals	Urban prosperity
E	Educated urbanites	Urban prosperity
F	Aspiring singles	Urban prosperity
G	Starting out	Comfortably off
H	Secure families	Comfortably off
I	Settled suburbia	Comfortably off
J	Prudent pensioners	Comfortably off
K	Asian communities	Moderate means
L	Post industrial families	Moderate means
M	Blue collar roots	Moderate means
N	Struggling families	Hard pressed
O	Burdened singles	Hard pressed

Additional Features: Discrete Socio-Economic Categories

		house_count
acorn_category	acorn_group	
Adversity	ACORN-K	165
	ACORN-L	342
	ACORN-M	113
	ACORN-N	152
	ACORN-O	103
	ACORN-P	110

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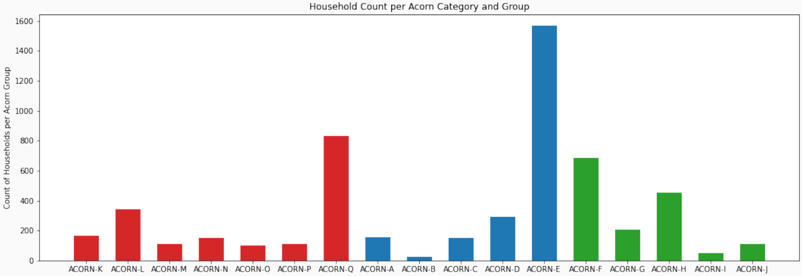

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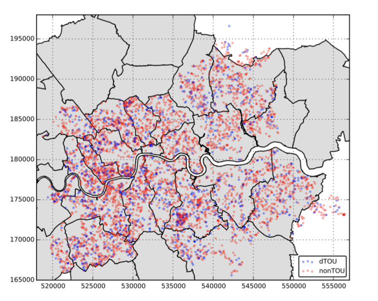
2. Some opted into the treatment group: subject to the dToU pricing model in 2013.

Low Carbon London Smart Meter Trial: Biases?

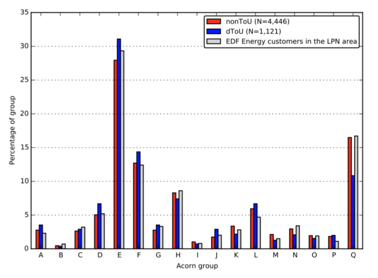
The treatment group was given some incentives:

- A guarantee that they will be reimbursed at the end of trial if they are worse off on the dToU tariff than they would have been on their previous tariff.
- Assurances regarding how many hours would be charged at the high price band.
- £100 for signing up to the dToU tariff.
- Another £50 for staying on the dToU tariff until the end of trial.
- Entry into a prize draw after completion of the post trial survey.

Low Carbon London Smart Meter Trial: Distribution?



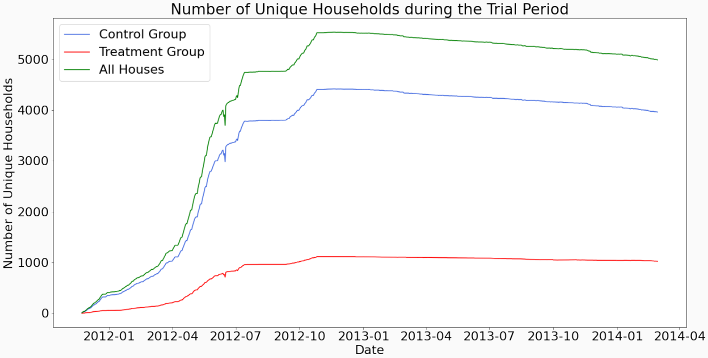
(a) Trial household sample locations overlaid on the borough boundary map of Greater London. This shows that the treatment and control group were representative samples of Greater London.



(b) The treatment and control groups were also representative socio-economic samples of Greater London.

Low Carbon London Smart Meter Trial: Missing Data

- 2012: Users were still onboarding.
- 2013: Some users dropped out of both the treatment and the control groups
- ~5,600 total households participated: ~4,500 were in the control group, ~1,100 were in the treatment group.



Treatment vs Control Group Baselines

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    - price sensitive group opted in
    - low consuming group opted in
    - those households are flexible time-wise: particular jobs, hours, etc.

The Math

Mathematical Model

Consider the following segmentation of the data.

- $\alpha_y :=$ control group's consumption matrix during year y
- $\beta_y :=$ treatment group's consumption matrix during year y

Dimenstionality Analysis: Control Group Matrices

$$\alpha_y = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n_c} \\ a_{21} & a_{22} & \cdots & a_{2n_c} \\ \vdots & \vdots & \ddots & \vdots \\ a_{t1} & a_{t2} & \cdots & a_{tn_c} \end{bmatrix}$$

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n_c is the number of households in the control group.

Dimenstionality Analysis: Treatment Group Matrices

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n_t is the number of households in the treatment group.

Mathematical Model

Year	Control Group	Treatment Group
2011	α_{2011}	β_{2011}
2012	α_{2012}	β_{2012}
2013	α_{2013}	$\hat{\beta}_{2013}$
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$\hat{\beta}_{2013}$ is the counterfactual consumption for β_{2013}.

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$T = \hat{\beta}_{2013} - \beta_{2013}$ is the treatment effect.

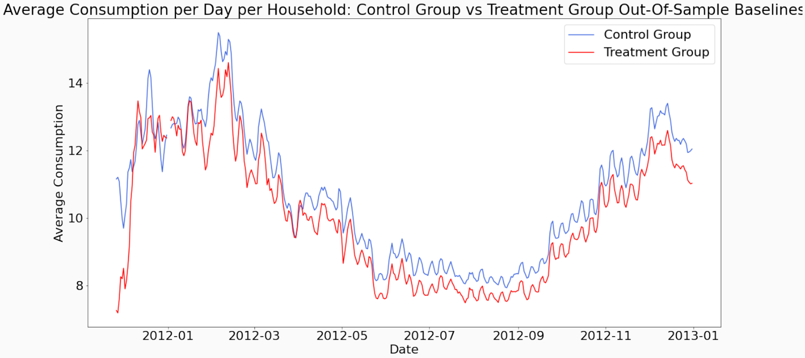
Goal is to **find a good estimate** for $\hat{\beta}_{2013}$.

Naive Model

If we didn't know about all these biases, we *could* use control group in 2013 as the counterfactual estimate for treatment group in 2013.

$$\begin{aligned} \hat{\beta}_{2013} &\approx \alpha_{2013} \\ T &= \beta_{2013} - \hat{\beta}_{2013} \\ &= \beta_{2013} - \alpha_{2013} \end{aligned} \tag{1}$$

Treatment vs Control Group Baselines



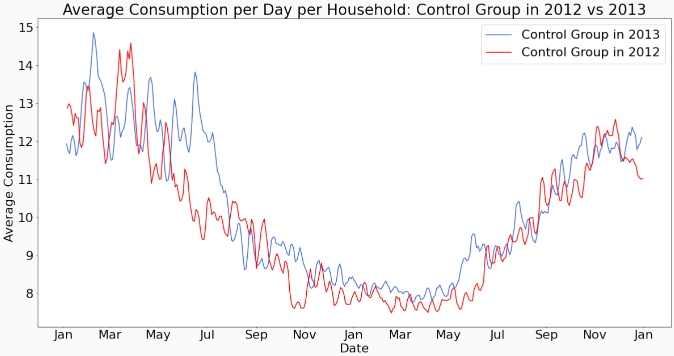
$\Longrightarrow$ the two groups don't have the same baseline electricity consumption patterns.

Sophisticated Naive Model

Let's instead use treatment group in 2012 as the counterfactual estimate for treatment group in 2013.

$$\begin{aligned} \hat{\beta}_{2013} &\approx \beta_{2012} \\ T &= \beta_{2013} - \hat{\beta}_{2013} \\ &= \beta_{2013} - \beta_{2012} \end{aligned} \tag{2}$$

Changes from Time: 2012 vs 2013



$\Longrightarrow$ Things changed between the two years even for the control group.

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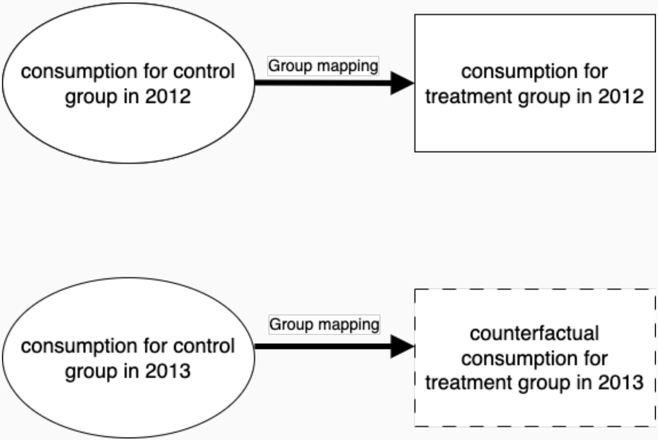

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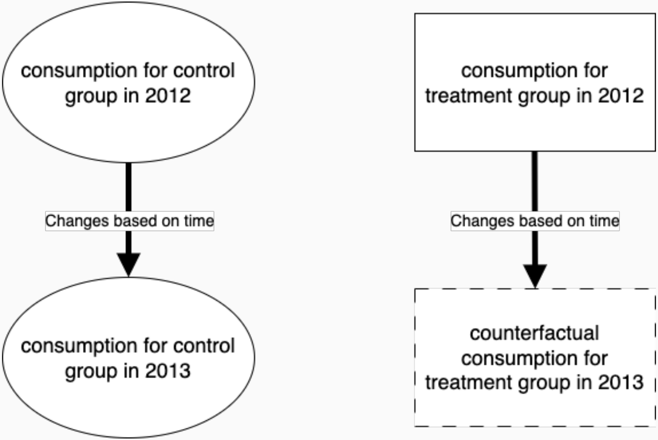

Mathematical Model: Using Group Mapping

$$
\begin{aligned}
\alpha_{2012} X &= \beta_{2012} \\
\alpha_{2013} X &= \hat{\beta}_{2013} \\
\Delta\text{treatment} &= \beta_{2013} - \hat{\beta}_{2013}
\end{aligned} \tag{3}
$$

The Analysis

Data Prep, Cleaning, Processing

UKPN-LCL-smartmeter-sample.csv	Nov 3, 2020 at 1:44 PM	1 MB	Comma...et (.csv)
Tariffs.xlsx	Jan 4, 2021 at 9:02 PM	235 KB	Microso...k (.xlsx)
Tariffs.csv	Jan 4, 2021 at 9:02 PM	371 KB	Comma...et (.csv)
tariffs_csv.csv	Jan 4, 2021 at 9:02 PM	371 KB	Comma...et (.csv)
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Power-Networks-LCL-June2015(withAcornGps)v2_141.csv	Aug 20, 2015 at 12:57 PM	68.8 MB	Comma...et (.csv)
Power-Networks-LCL-June2015(withAcornGps)v2_140.csv	Aug 20, 2015 at 12:56 PM	68.8 MB	Comma...et (.csv)
Power-Networks-LCL-June2015(withAcornGps)v2_139.csv	Aug 20, 2015 at 12:56 PM	68.7 MB	Comma...et (.csv)
Power-Networks-LCL-June2015(withAcornGps)v2_138.csv	Aug 20, 2015 at 12:55 PM	68.9 MB	Comma...et (.csv)

Data Prep, Cleaning, Processing

1. first set of files, segmented by year, contain the `house_id` (str), `treated` (bool), `date_time` (datetime), `KWH/hh` (float).

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3. third is the tarrif file contains `date_time` (datetime), price per designation for that hh (float).

Data Prep, Cleaning, Processing

Name	Date Modified	Size	Kind
tariffs.gzip	Mar 29, 2021 at 9:51 PM	108 KB	gzip co...archive
total_acorn.gzip	May 16, 2021 at 4:30 PM	30 KB	gzip co...archive
total_usage_2011.gzip	Mar 2, 2021 at 12:18 AM	628 KB	gzip co...archive
total_usage_2012.gzip	Apr 26, 2022 at 7:30 PM	185.2 MB	gzip co...archive
total_usage_2013.gzip	Apr 26, 2022 at 10:28 AM	298.9 MB	gzip co...archive
total_usage_2014.gzip	Apr 26, 2022 at 10:28 AM	20.9 MB	gzip co...archive
total_usage.gzip	Mar 2, 2021 at 12:16 AM	549.6 MB	gzip co...archive

If we look at percent change without normalizing the baselines the treatment was effective.

Other Clustering?

I used different clustering methods to cluster houses in this data set based on the control group's consumption pre-intervention: k-means clustering, PCA3, TSNE4. I also tried clustering on the frequency responses which I found fast Fourier trans- form. PCA, TSNE, and Agglomerative clustering on the resulting data set was also inconclusive. This is reason for sticking to the pre-existing socio-economic clusters.

Assume matrix $\alpha^{t \times n_c}$ contains control group data, and $\beta^{t \times n_t}$ contains treatment group data. Where $t = 365 \times 48 = 17520$, n_c is the number of households in the control group and n_t is the number of households in the treatment group.

$$\begin{aligned} \overline{\beta^m_{2012}} &= a \times \overline{\alpha^m_{2012}} + b \\ \overline{\hat{\beta}^m_{2013}} &= a \times \overline{\alpha^m_{2013}} + b \\ \overline{\Delta \text{treatment}} &= \overline{\beta^m_{2013}} - \overline{\hat{\beta}^m_{2013}} \end{aligned} \tag{4}$$

The Conclusion

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    - How does that impact your analysis and results?

Takeaways

- KYD: know your data: learn how it was collected, its biases, shortcomings, feature space, problem space.

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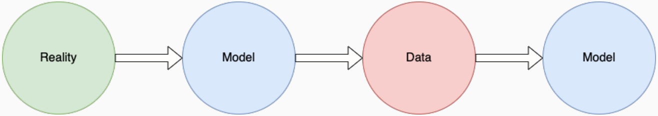
- KYD: know your data: learn how it was collected, its biases, shortcomings, feature space, problem space.
- Before diving into fitting a model to your data, it's important to base your analysis on some mathematical model



Thank You! Questions?

- https://github.com/sabanejad
- https://www.linkedin.com/in/sabanejad/