Robust Short Term Load Forecasting

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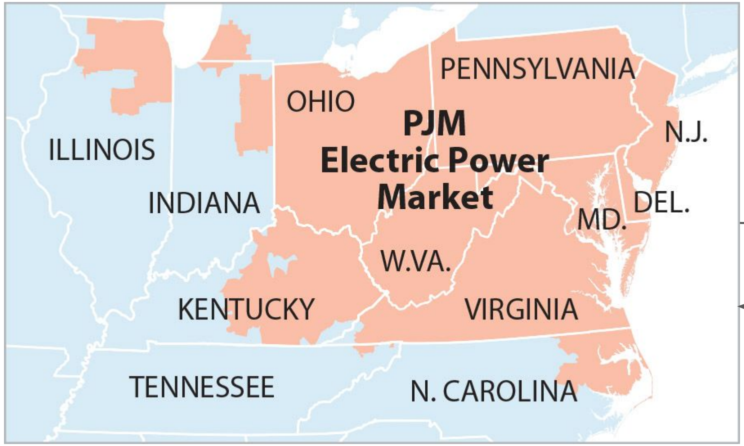
Problem Background



Serves

Buys from

PJM (Regional transmission organization)

- *Operates grids*
- *Dispatches power plants*
- **Runs electricity market**

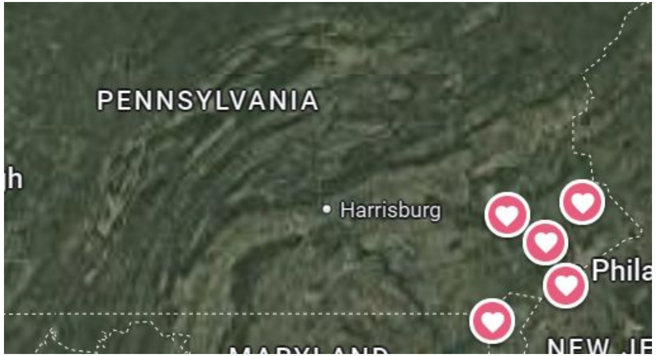
PECO (Electric utility; Us)

- **Predicts and buys electricity from PJM day-ahead**
- *Delivers electricity to users*

Dataset

- Historical hourly metered load (MW)
  - Source: PJM
  - Time range: From 2010's to present
  - Area scope: Philadelphia Electricity (~2100 square miles)
  - Time resolution: hourly

- Weather (temperature, wind speed, humidity…)
  - Source: Open-meteo
  - Estimated at different locations in PA
  - Also hourly



The temperature of marked places are used

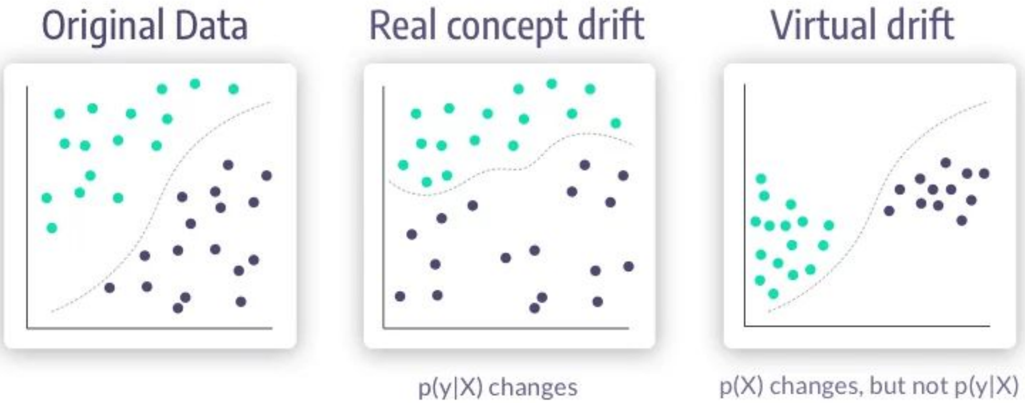
- Holiday/Weekend?
- Before/during/after COVID-19?
- ……

Goal: probabilistic interval prediction

- Motivation: imbalance cost of underestimating v.s. overestimating
- Underestimate day-ahead → buy more at last minute → 10x more expensive
  - On the other hand, overestimate isn’t as costly
  - Upper confidence bound (e.g. 95% quantile) is very important

- Goal: output sharp and calibrated probabilistic interval of 2026 loads day-ahead
  - Sharp: small interval length
  - Calibrated: probabilistic claim matches empirical coverage

Challenges



- Concept drift of p(y|x)
  - COVID-19
  - Policy changes
  - Increase of electric cars
  - How do we adapt to the latest concept shift without much data under the shift?

- Few-shot predictions
  - < 20 data points for all holidays, the most volatile days
  - How to sharpen their predicted intervals, while still guarantee calibration?

Tentative Pipeline

1. Feature engineering and a simple regression baseline
    a. Goal: beating simple baseline (more on next slide)

2. Switching to probabilistic forecast
    a. Pinball loss
    b. Conformal prediction (time series version of which to be found)
    c. Goal: beat baseline (to be found)

3. Quantify and address concept shift
    a. Compare performance on immediate/remote future test data
    b. Prioritize recent training data

4. Improve few-shot prediction
    a. Group holidays together
    b. Separate model for holidays

Simple Regression Baseline

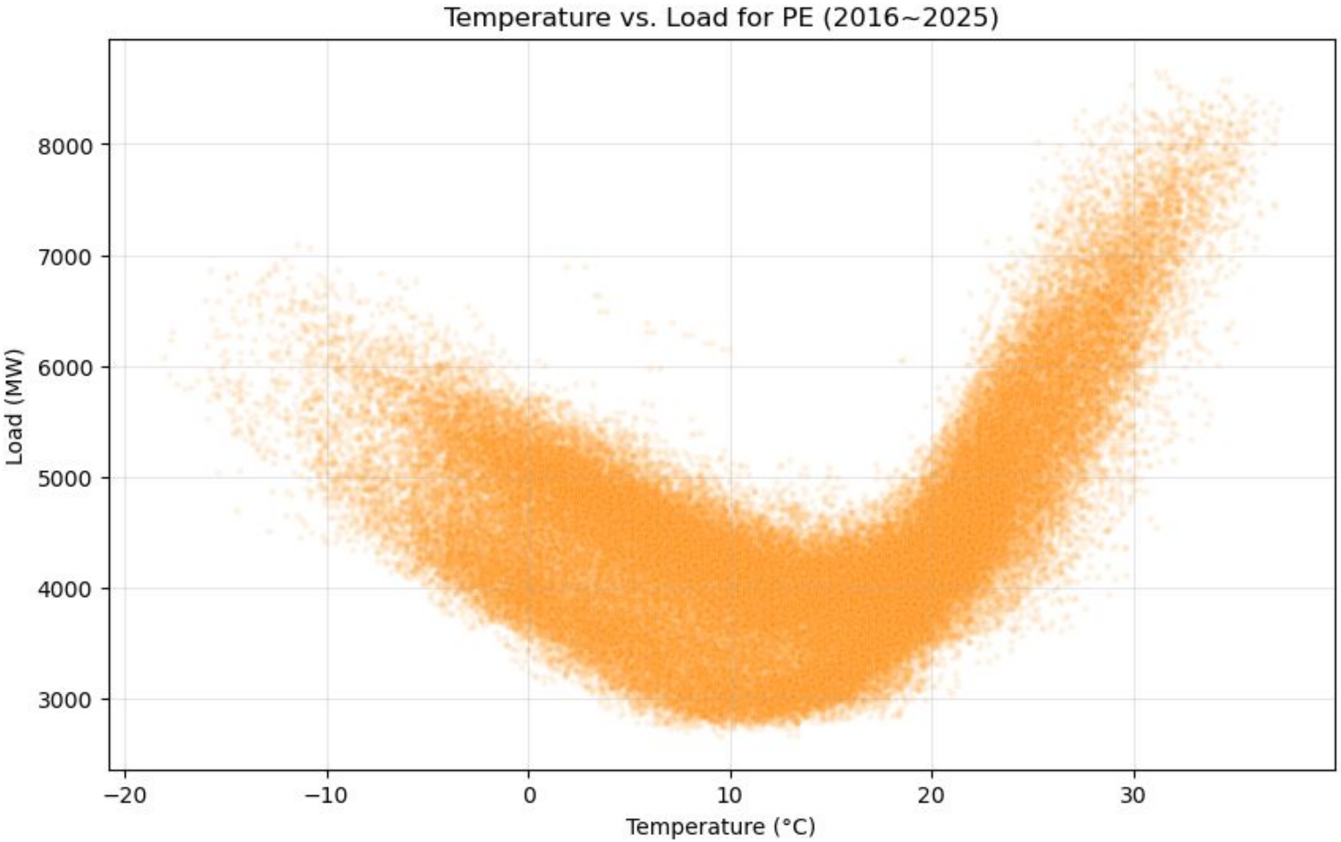
- Linear regression
- Heavy feature engineering
  - 3rd order polynomial
  - Trend term（$Trend_{t=0}$ = 0; $Trend_{t=1}$ = 1; $Trend_{t=2}$ = 2…)
  - Feature interaction terms
- Mean Absolute Percentage Error (MAPE; Error / True_Value): 4.98%
- Adaptation to probabilistic forecast
  - Pinball loss
  - Conformal prediction

$$\mathrm{E}(Load) = \beta_0 + \beta_1 \times Trend + \beta_2 \times Day \times Hour + \beta_3 \times Month + \beta_4 \times Month \times TMP + \beta_5 \times Month \times TMP^2 + \beta_6 \times Month \times TMP^3 + \beta_7 \times Hour \times TMP + \beta_8 \times Hour \times TMP^2 + \beta_9 \times Hour \times TMP^3, \quad (16)$$

Dataset exploration: temperature correlation

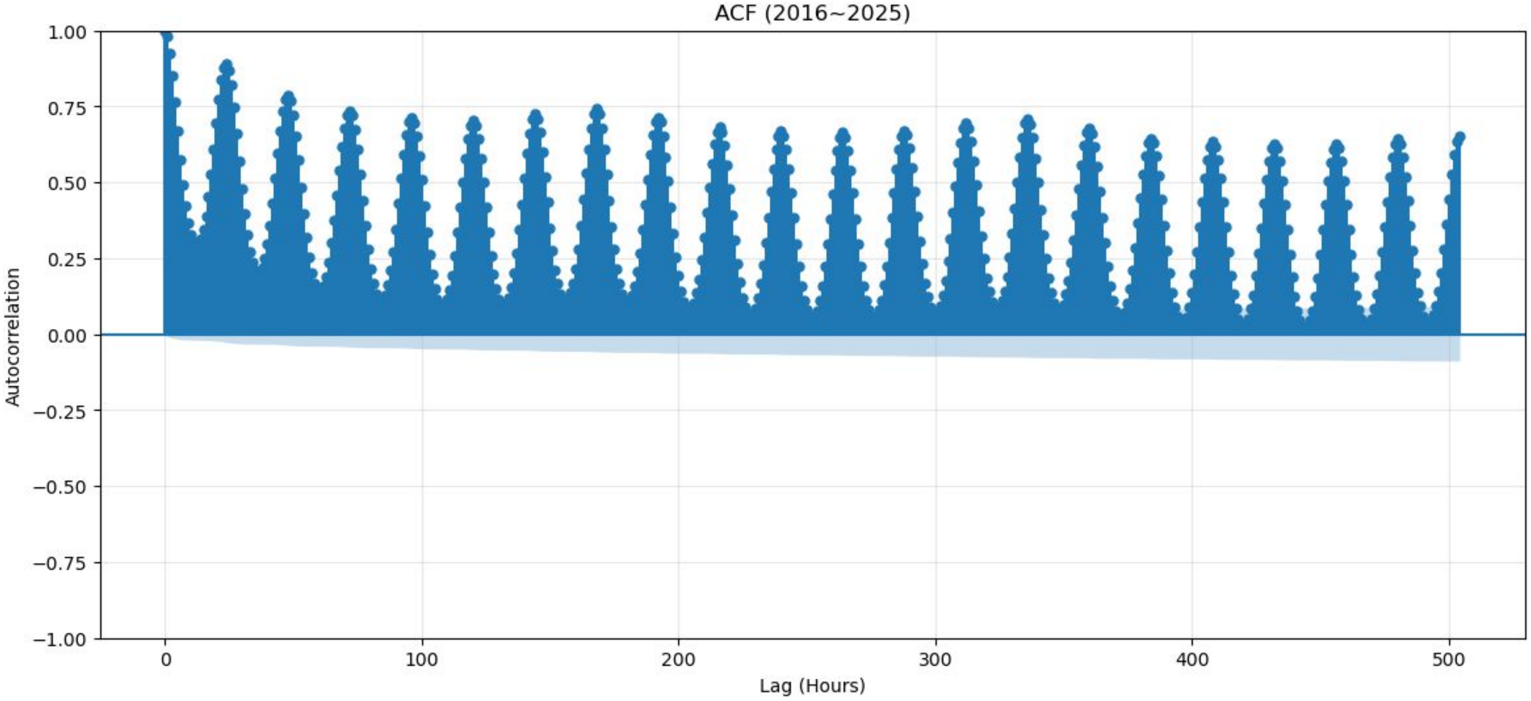
Heat/cold → high load

Results in yearly seasonality



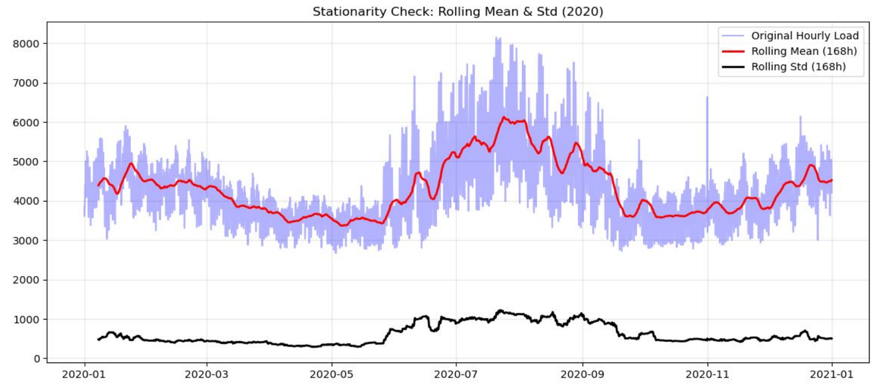
Autocorrelation

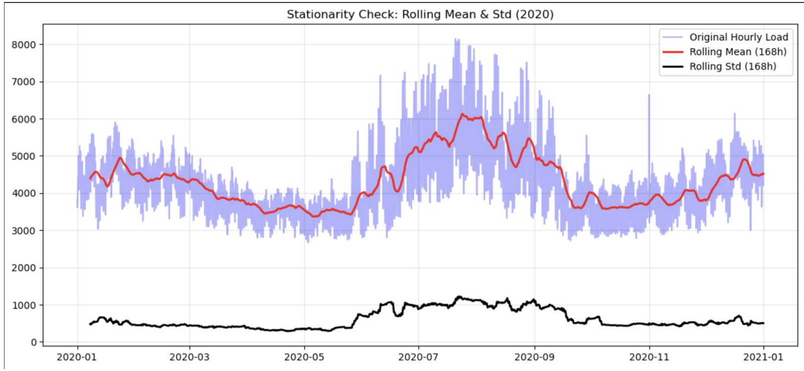
Autocorrelation peaks every 24 hours, decaying

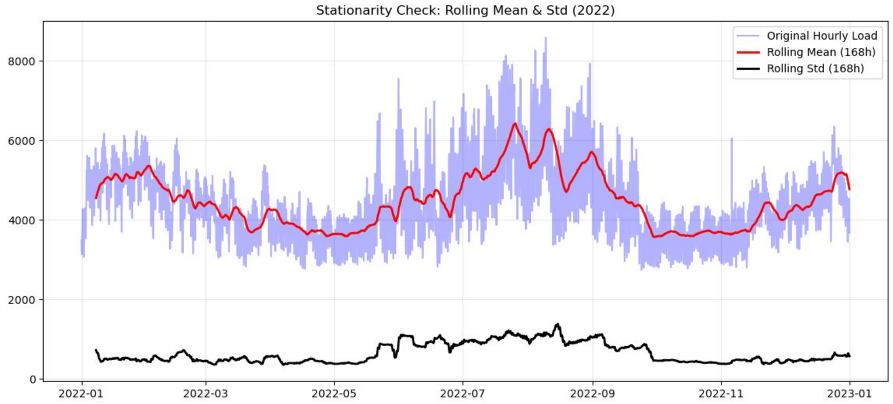


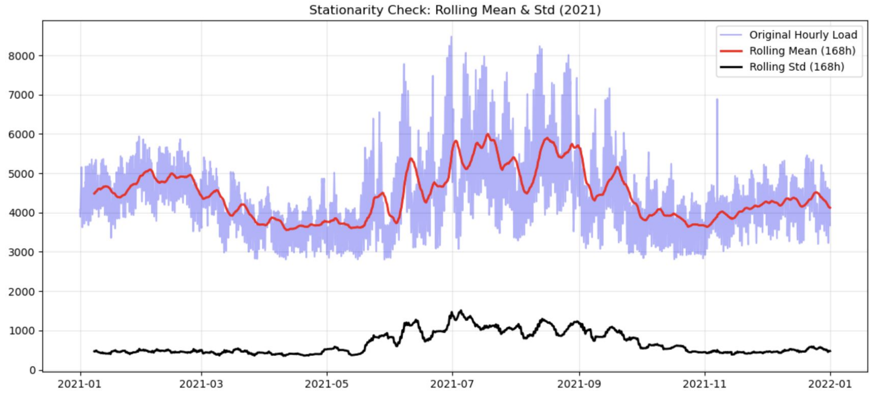
Yearly seasonality

2 peaks: Jan and August



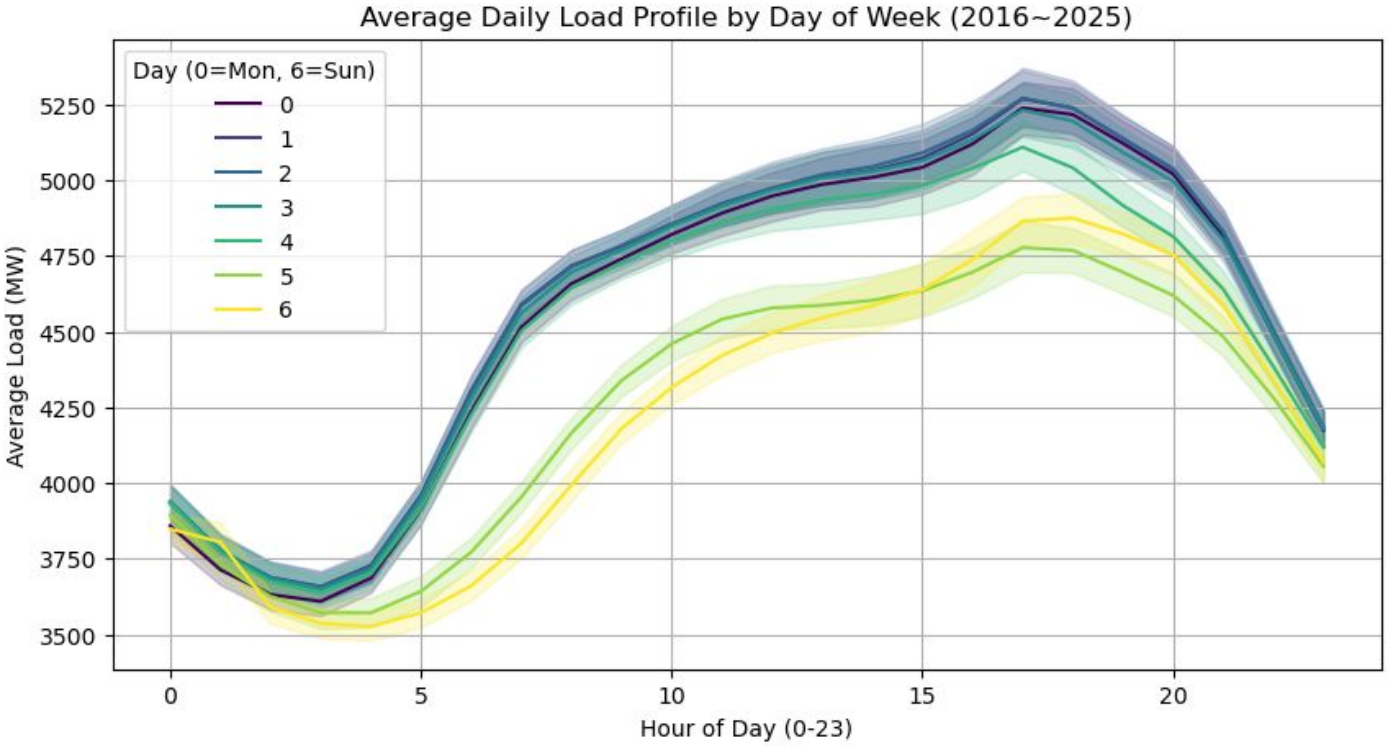






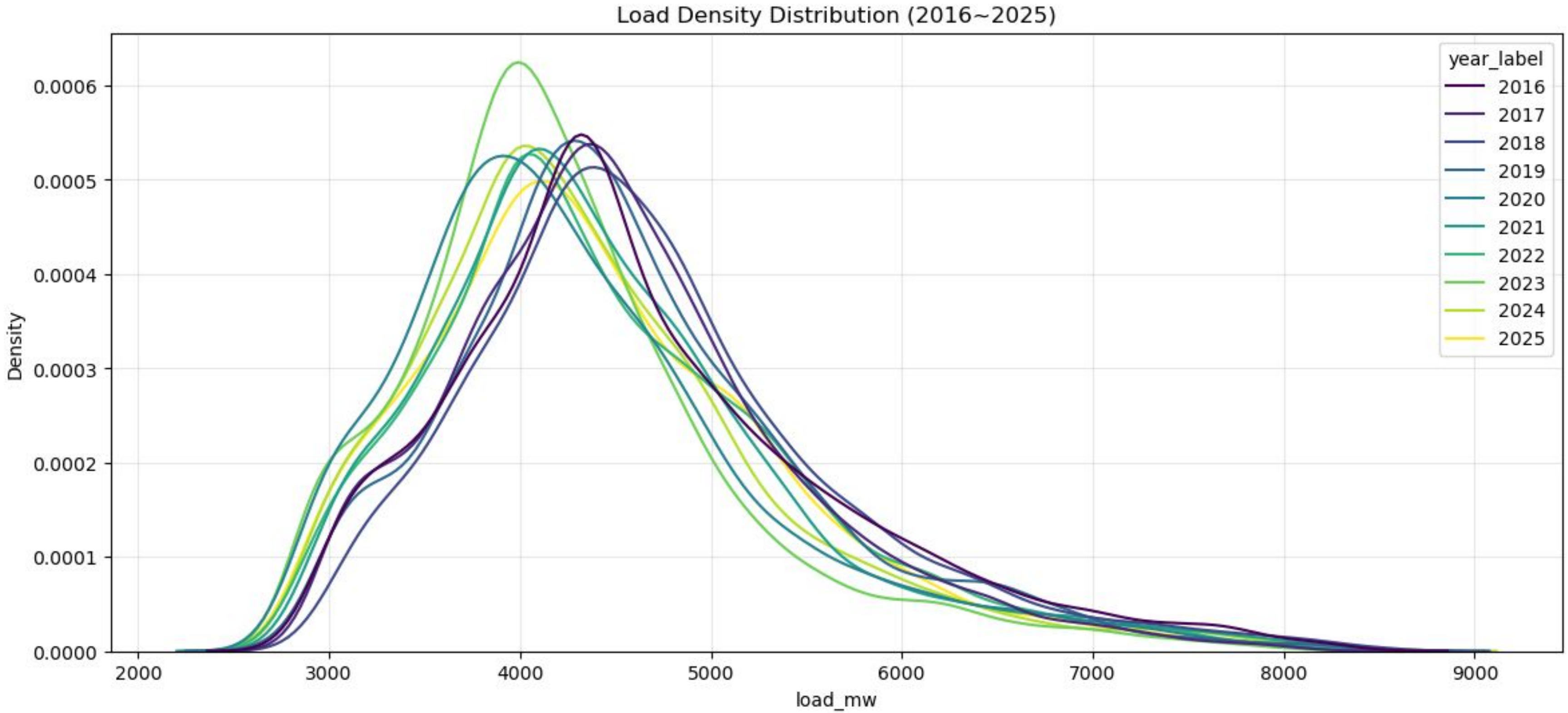
Weekly seasonality

Weekday > Weekend



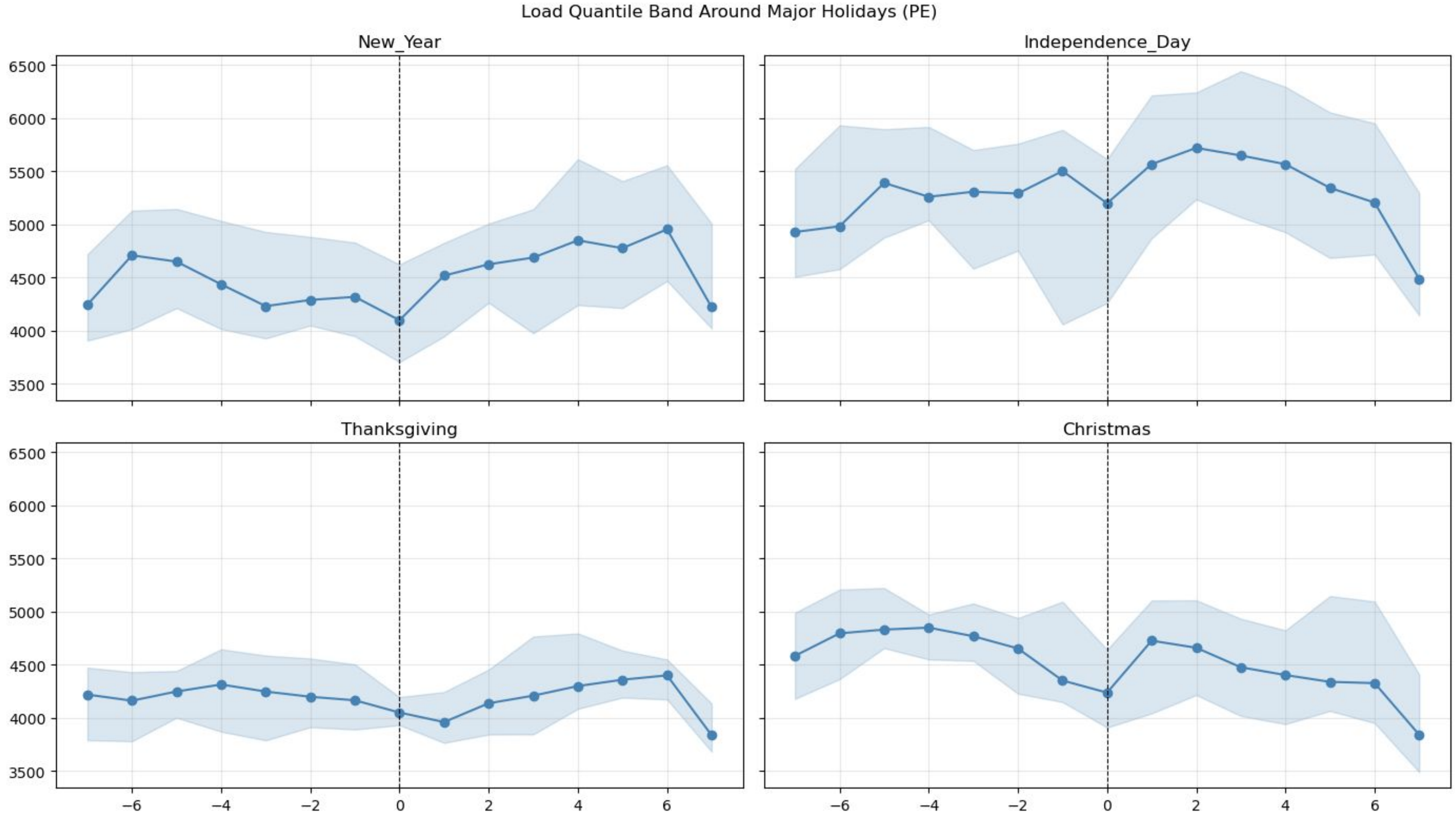
Load density distribution shift

The electricity load is decreasing distribution-wise



Holidays

Surprisingly smooth!

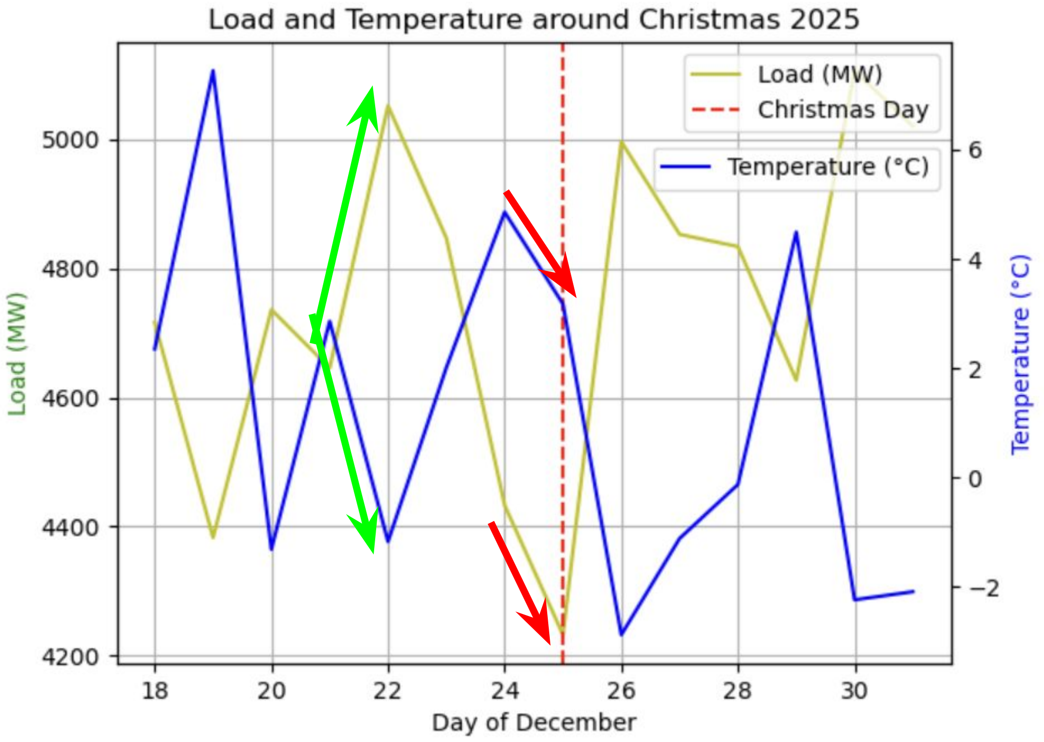


Holidays

However, the ”physics“ may still change in holidays
, which may or may not be learnt with few data points

Normal correlation

Holiday correlation



Thank you for listening!