Energy Market Analysis Using Kernel Methods

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Outline

Motivation

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Objectives

Pinball loss

The pinball score or quantile score is used to measure the accuracy of a quantile forecast.

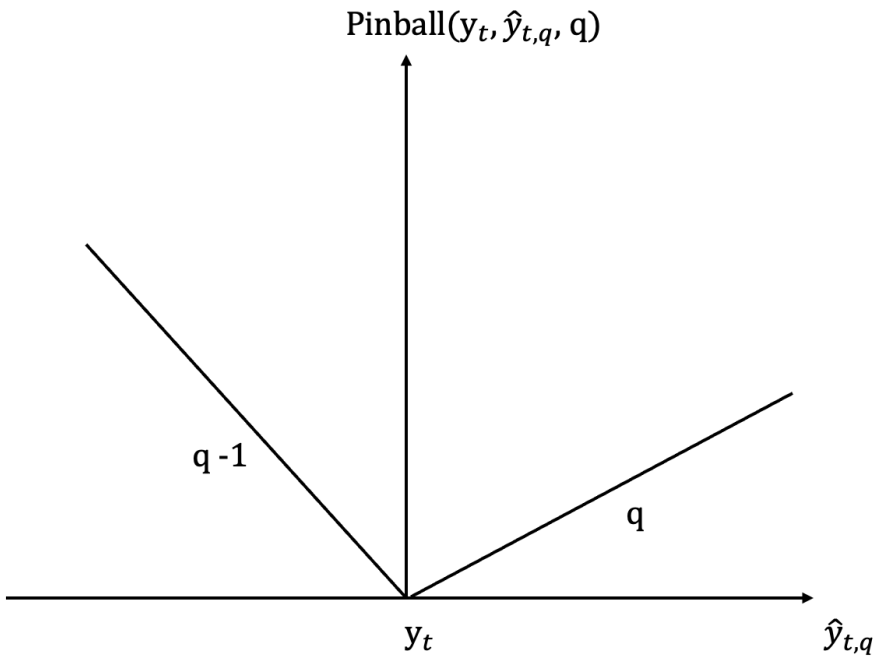
Definition

The pinball loss is defined as

$$\text{Pinball}(y_t, \hat{y}_{t,q}, q) = \begin{cases} (q-1)(\hat{y}_{t,q} - y_t) & y_t > \hat{y}_{t,q} \\ q(\hat{y}_{t,q} - y_t) & y_t \leq \hat{y}_{t,q} \end{cases}$$

Pinball loss

The pinball loss is an asymmetric function, it weights its score differently depending on the error sign and on the quantile considered. By averaging all the pinball losses over all quantiles and over the whole forecast horizon, we obtain the pinball loss of the probabilistic forecast.



Continous ranked probability score

The continous ranked probability score (CRPS) measures the difference between the estimated cumulative distribution $\hat{F}$ and the empirical cumulative density function (CDF).

Definition

The continous ranked probability score is defined as

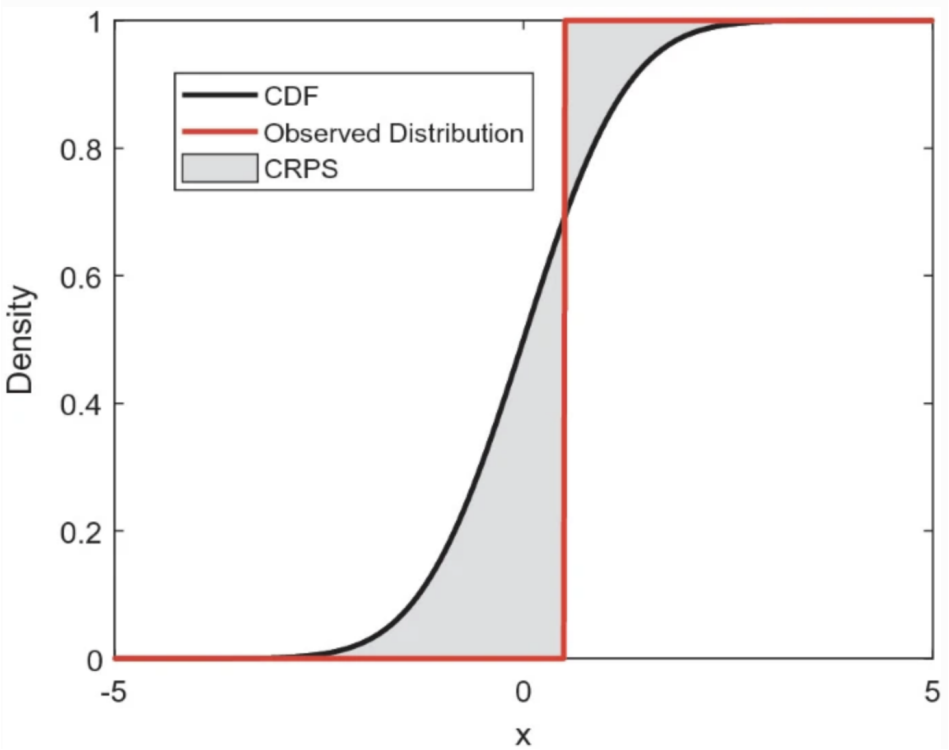
$$\mathrm{CRPS}(y, \hat{F}) = \int_{-\infty}^{\infty} \left(\hat{F}(x) - \mathbb{I}_{\{x-y\}} \right)^2 dx$$

Where the indicator function is defined as

$$\mathbb{I}_{\{z\}} = \begin{cases} 0, & z < 0 \\ 1, & z \geq 0 \end{cases}$$

Continous ranked probability score

For a visualisation see Figure. The grey area is what contributes toward the CRPS score. The better the estimated cumulative density function is the smaller the total CRPS score will be.



Results

- We have studied kernel methods for electricity forecasting both in the point and probabilistic framework.
- We provided a Python open source implementation for kernel quantile regression compatible with the sklearn API. The code has been packaged and uploaded to the Python Package Index (PyPI) with the name kernel-quantile-regression. The github repo hosting the source code includes also the script implementing the experiments along with the cleaned datasets; this contribution is intended to forster reproducibility in research.
- We achieved superior performance of kernel quantile regression compared to standard quantile regressor algorithms.
- We created and made available datasets suitable for algorithms benchmarking considering data from the DACH region (Germany, Switzerland and Austria). The format of these data takes inspiration from the popular GEFCom competitions.
- Kernel quantile regression extensive comparison between kernel function types.
- We compared kernel quantile regression against state of the art probabilistic algorithms in the literature by means of the GEFCom2014 competition.

Thank you