Forecating the electricity consumption by aggregating specialized experts

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We consider the empirical goal of sequential short-term (one-day ahead) forecasting of electricity consumption. For this purpose, we look at a recent data set used by EDF R&D to forecast the French market. It contains the observed electricity load as well as some side information (temperature, date,...). We intend to work in real operating conditions and we restrict our attention to operational constraints which come with it (delays for data acquisition). To achieve our goal we have in mind a two-step approach.

Construction of heterogenous base forcasters

First of all we build in this study a set of base forecasters, that aim to be as heterogenous as possible and to exhibit varied enough behaviors. They aspire also to be optimized for specific situations depending the side information (weather, special events).

To do so, we first test on our dataset several recent machine learning algorithms, such as Boosting or Random-Forests respectively introduced by Freund and Schapire [1997] and Breiman [1996]. We furthermore consider statistical models used by EDF R&D that come from three main categories: parametric, semi-parametric, and non-parametric models – see Bruhns et al.

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[2005], Pierrot et al. [2009], Wood [2006], and Antoniadis et al. [2006]. So as to specialize our forecasters, we focus their training sets on subsets depending on the specialization they aim to acquire. We also get more diversity by letting the parameters of the models vary.

Online mixture of the base forecasters

In a second step, we apply the framework of prediction with expert advice well summarized in Cesa-Bianchi and Lugosi [2006]. We combine in a sequential fashion all these base forecasts, so as to optimize our forecasting of electricity consumption. We refer the interested reader to Devaine et al. [2012a] for a more detailed description.

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