# Adaptive Methods for Short-Term Electricity Load Forecasting During COVID-19 Lockdown in France

Yannig Goude, joint work with Joseph de Vilmarest and David Obst see https://arxiv.org/pdf/2009.06527.pdf

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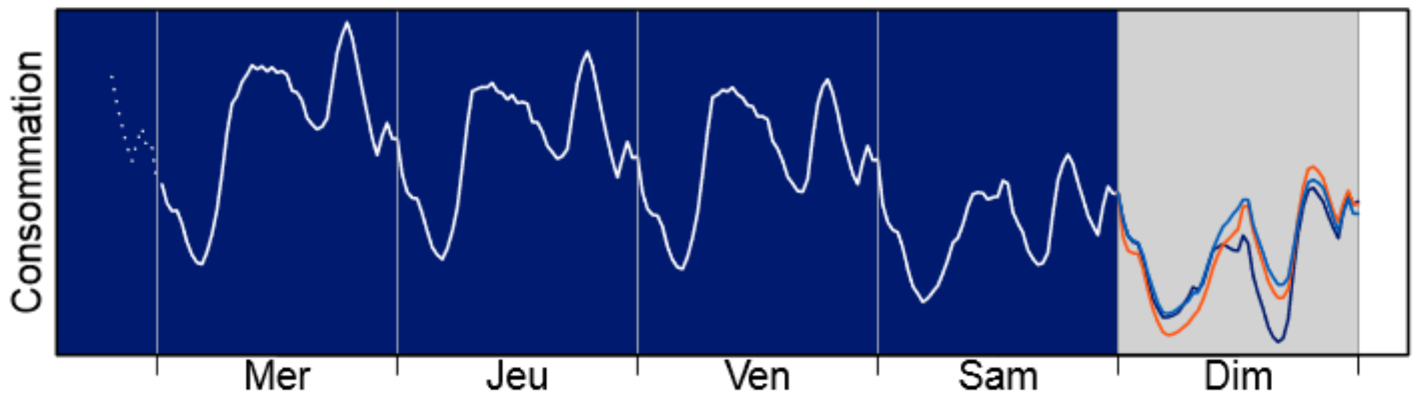
**Data Science at Electricity Providers by Avalon local group of the Royal Statistical Society, 29th September 2020**

# Load forecasting is crucial for electrical power system operations

- Generation: optimising production planning
- Trading: buy and sell electricity on the markets
- Grid management: transmission, distribution



# COVID-19 pandemic impacted our social and economical life

# Electricity production and consumption were of course affected

We will present and discuss:

- **Problems**: How does it impact electricity load in the world, in France in particular
- **Model design**: How the forecasting model could be adapted to maintain good forecasting performances during (and after…) that period, what we did at EDF and other related works
- **Data**: what kind of data could be used to improve forecasts

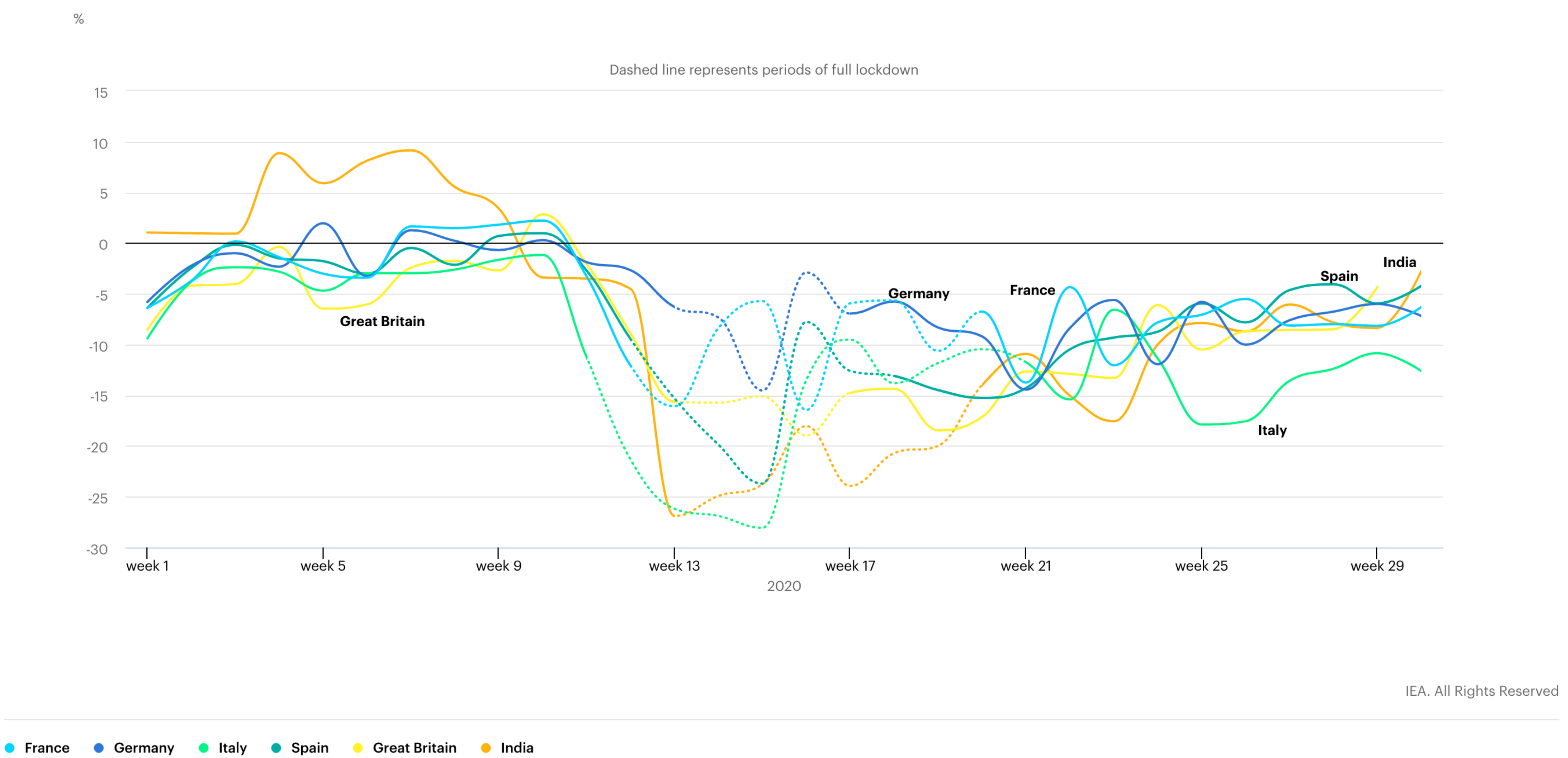
# Problems, Electricity Data

# How does it impact electricity load in the world?

Electricity demand dropped quickly with confinement measures.

It steadily recovered as measures were gradually softened; it was still 10% below 2019 levels in EU countries in June.

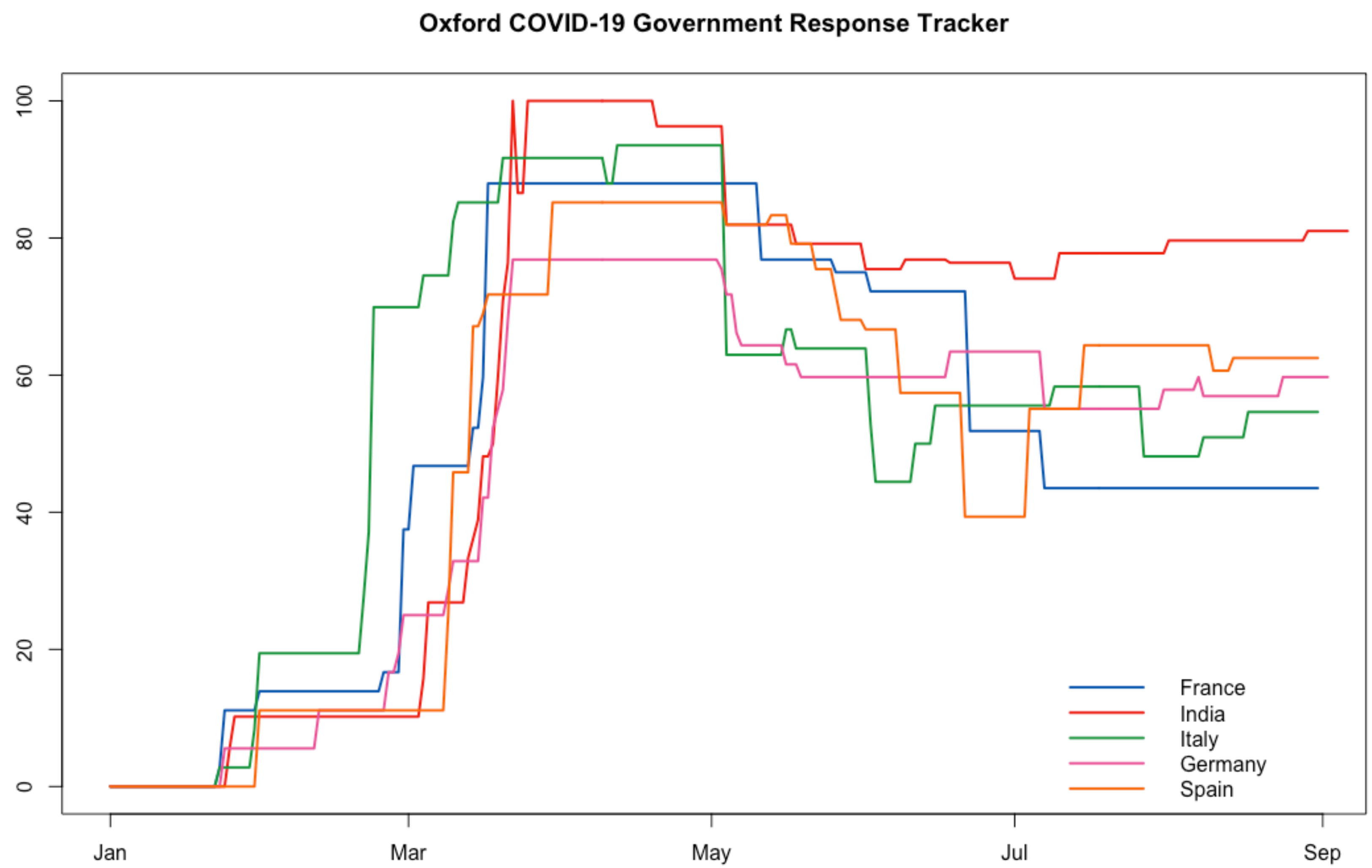
In the last week of July, electricity demand was 5% below 2019 levels in EU countries except Italy. In India, recovery seems faster.




IEA, Year-on-year change in weekly electricity demand, weather corrected, in selected countries, 2020, IEA, Paris
https://www.iea.org/data-and-statistics/charts/year-on-year-change-in-weekly-electricity-demand-weather-corrected-in-selected-countries-2020

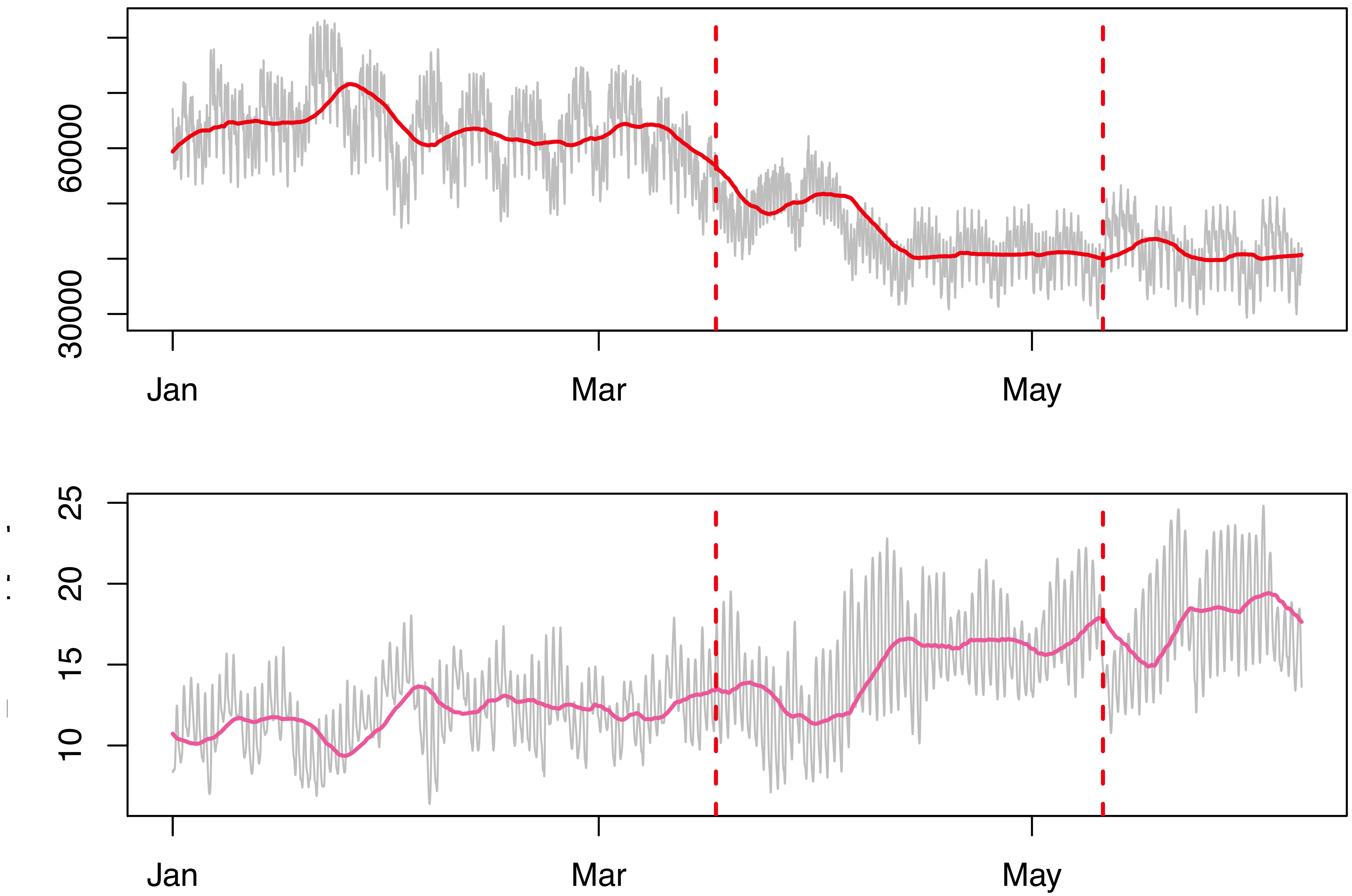
# Government responses of different intensities

| | First lockdown measures (day 0) | Lockdown strengthened | Lockdown softened |
|---|---|---|---|
| **France** | March 14 | March 17 (day 3) | May 11 (day 55) |
| **Germany** | March 15 | March 22 (day 7) | April 20 (day 36) and May 4 (day 50) |
| **Italy** | March 4 | March 13 (day 9) | April 14 (day 41) and May 4 (day 61) |
| **Spain** | March 9 | March 15 (day 6) | May 11 (day 55) |
| **UK** | March 19 | March 23 (day 4) | May 11 in England (day 55) |
| **India** | March 18 | March 25 (day 7) | May 4 (day 47) |

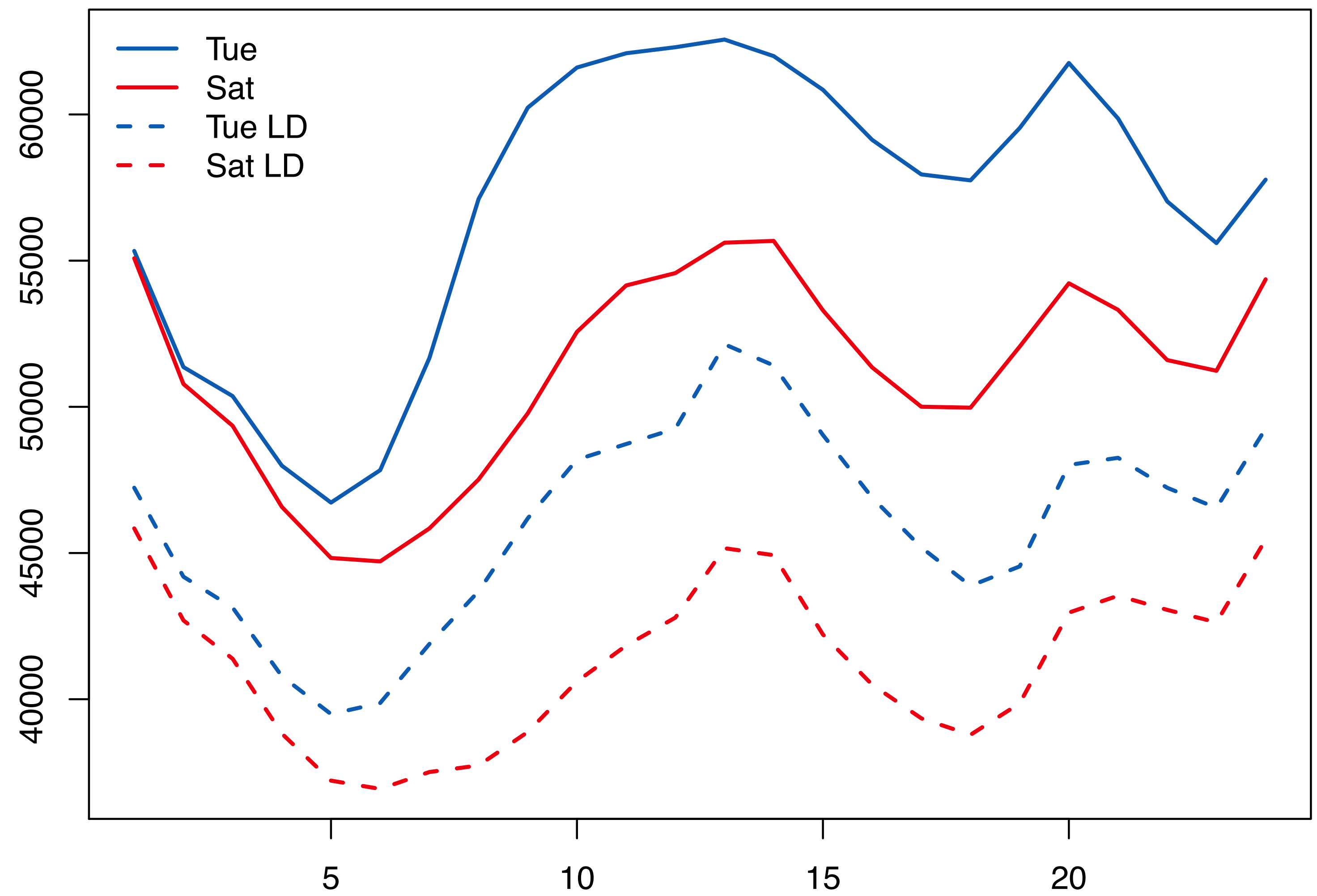



https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker

# How does it impact electricity load in the France?

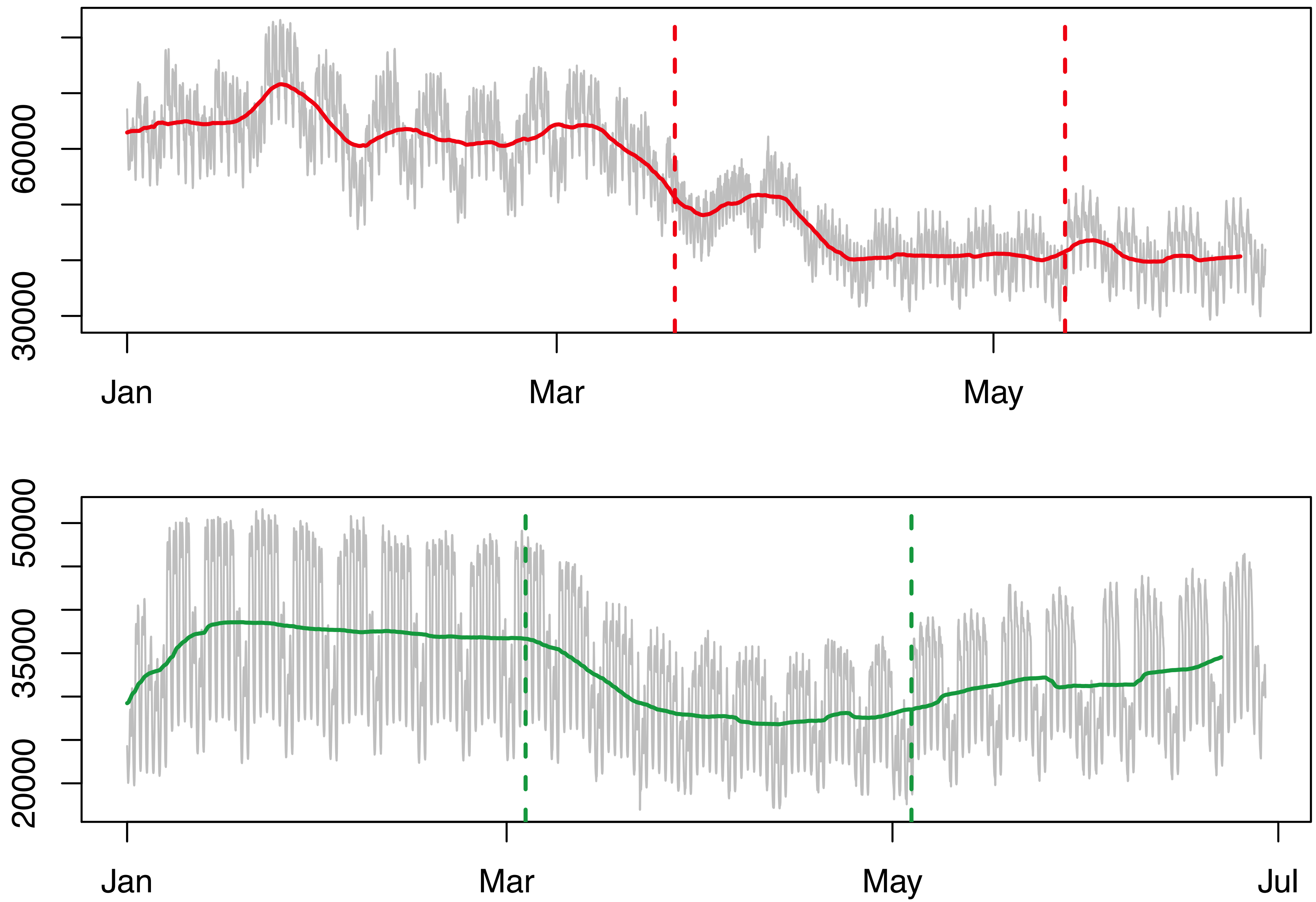



Half-Hourly french electricity load consumption (top) and temperature.

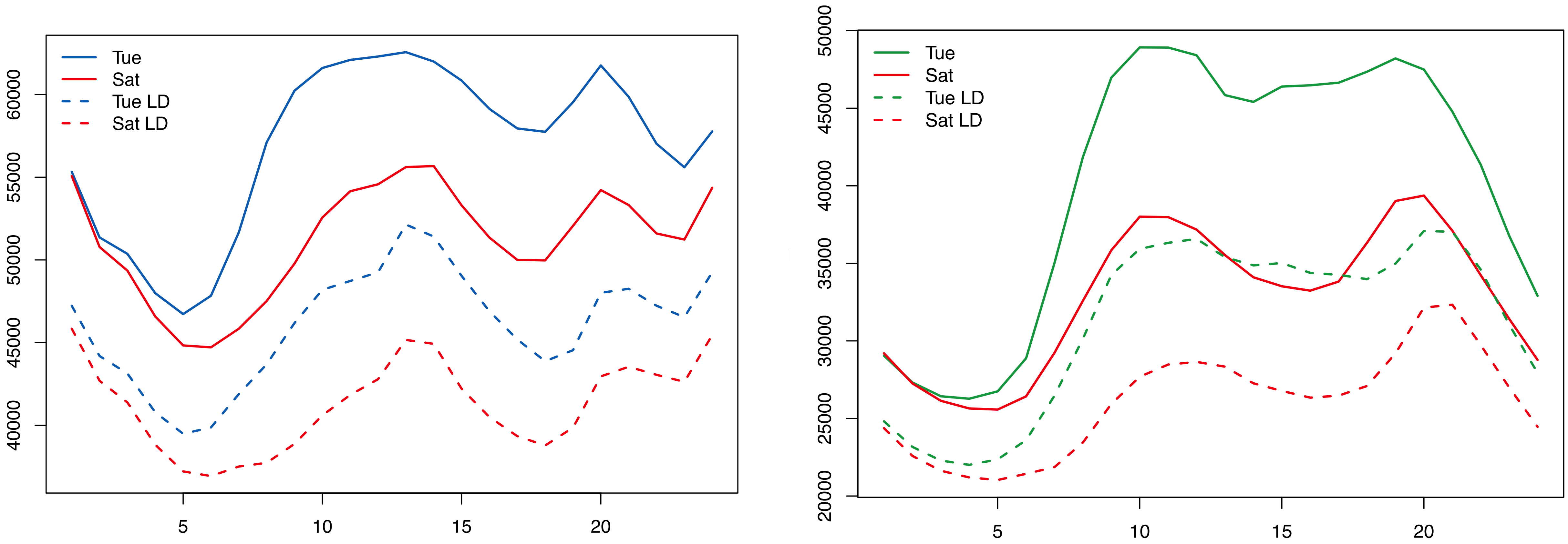



French electricity Tuesday and Saturday load profilesbefore and during the lockdown (Dashed lines).

# Comparison with Italy




French and Italian electricity load (in MW) at resp. half-hourly and hourly resolution in 2020. Dashed lines are the starting and ending date ofthe lockdown



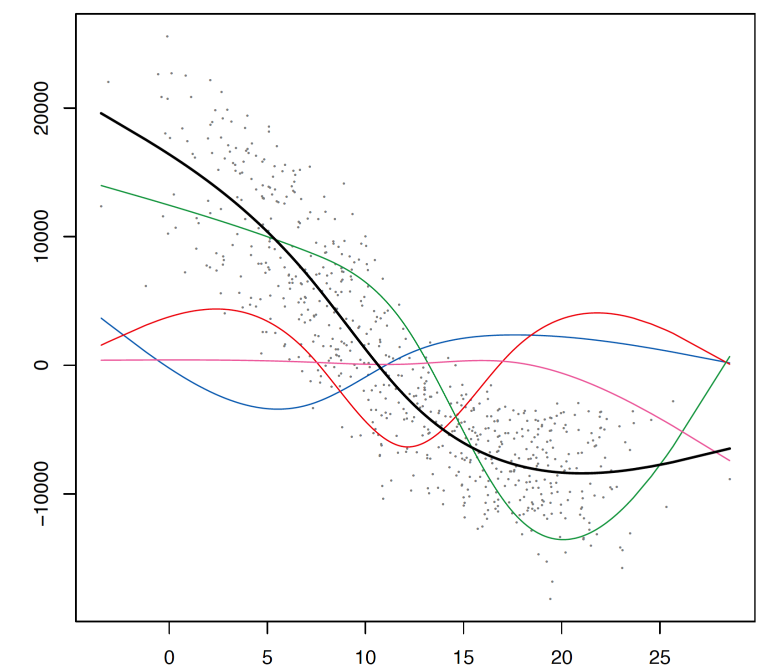

French and Italian electricity Tuesday and Saturday load profiles before and during the lockdown (Dashed lines)

# Algorithms and models

# Our forecasting model

We model the electricity consumption with GAM, a sum of linear and smooth additive effects (see Hastie & Tibshirani (1990) and Wood (2017))

$$
\begin{aligned}
y_t = & \sum_{i=1}^{7}\sum_{j=0}^{1} \alpha_{i,j} \mathbb{1}_{\text{DayType}_t = i} \mathbb{1}_{\text{DLS}_t = j} \\
& + \sum_{i=1}^{7} \beta_i \text{Load1D}_t \mathbb{1}_{\text{DayType}_t = i} + \gamma \text{Load1W}_t \qquad (1) \\
& + f_1(t) + f_2(\text{ToY}_t) + f_3(t, \text{Temp}_t) + f_4(\text{Temp95}_t) \\
& + f_5(\text{Temp99}_t) + f_6(\text{TempMin99}_t, \text{TempMax99}_t) + \varepsilon_t ,
\end{aligned}
$$

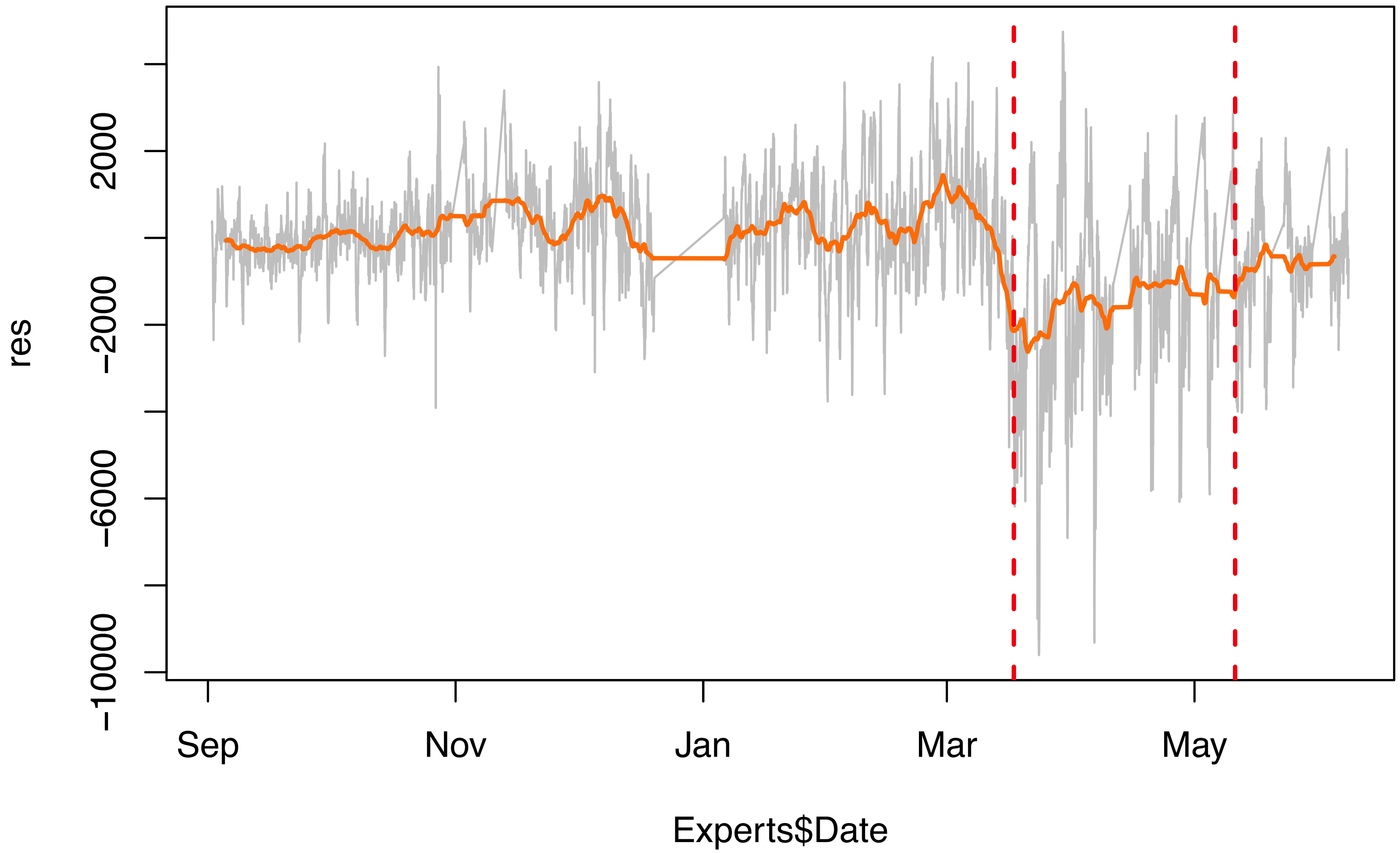



Each effect is obtained by penalised spline regression, minimising a GCV criteria to calibrate the amount of smoothness:

$$\sum_{i=1}^{n}(y_i - \beta_0 \mathbf{X}_i^0 - \sum_{q=1}^{p} f_q(x_i))^2 + \sum_{q=1}^{p} \lambda_q \int |||f_q^{''}(x)|||^2 dx$$

$$f_j(x_j) = \sum_{i=1}^{k} \beta_{ji} b_{ji}(x_j).$$

# Of course achieve bad performances after the lockdown




MAPE increases from
1.4% to 3.8%

# Online update

- We model the electricity consumption as a sum of time varying additive effects:

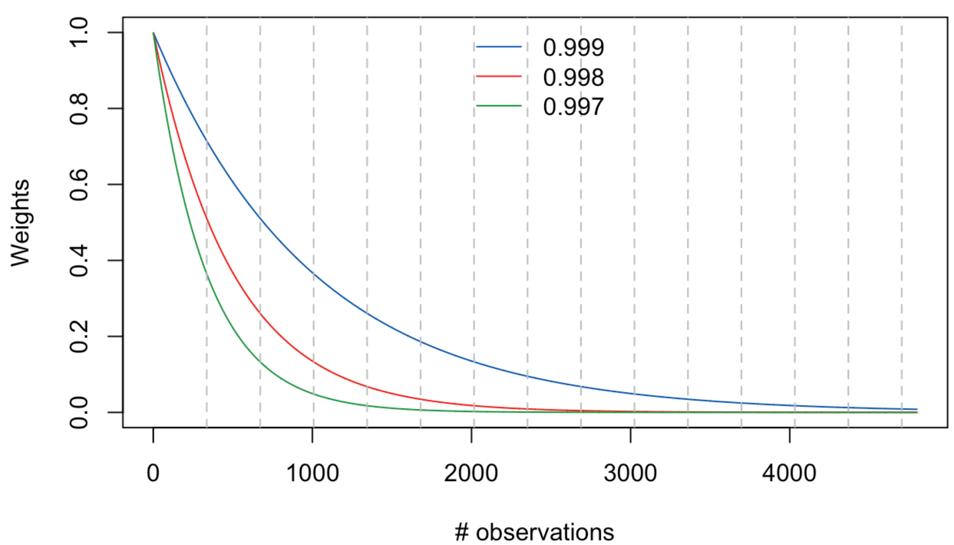
$$\mathbb{E}[y_t] = f_t(\boldsymbol{x}_t)$$

- For stability reasons and a good reactivity to changes we restricted to this special case:

$$\mathbb{E}[y_t] = \boldsymbol{\theta}_t^\top f(\boldsymbol{x}_t)$$

- And the time varying coefficients are estimated solving an iterative least square problem with a forgetting factor

$$\hat{\boldsymbol{\theta}}_t = \arg\min_{\boldsymbol{\theta}\in\mathbb{R}^d} \sum_{s=1}^{t-1} e^{-\mu(t-s)} \left(y_s - \boldsymbol{\theta}^\top f(\boldsymbol{x}_s)\right)^2$$




Ba, A., Sinn, M., Goude, Y., & Pompey, P. (2012).

# Online update

$$y_t = \boldsymbol{\theta}_t^\top f(\boldsymbol{x}_t) + \varepsilon_t \,,$$
$$\boldsymbol{\theta}_{t+1} = \boldsymbol{\theta}_t + \boldsymbol{\eta}_t \,,$$

$(\varepsilon_t)$ and $(\boldsymbol{\eta}_t)$ are gaussian white noises

variance / covariance $\sigma^2$ and $Q$

**Algorithm 1:** Kalman Filter

**Initialization**: the prior $\boldsymbol{\theta}_1 \sim \mathcal{N}(\hat{\boldsymbol{\theta}}_1, P_1)$ where $P_1 \in \mathbb{R}^{d \times d}$ is positive definite and $\hat{\boldsymbol{\theta}}_1 \in \mathbb{R}^d$.

**Recursion**: at each time step $t = 1, 2, \ldots$

1) Prediction:

$$\mathbb{E}\left[y_t \mid (\boldsymbol{x}_s, y_s)_{s<t}, \boldsymbol{x}_t\right] = \hat{\boldsymbol{\theta}}_t^\top f(\boldsymbol{x}_t) \,,$$
$$Var\left[y_t \mid (\boldsymbol{x}_s, y_s)_{s<t}, \boldsymbol{x}_t\right] = \sigma^2 + f(\boldsymbol{x}_t)^\top P_t f(\boldsymbol{x}_t) \,.$$

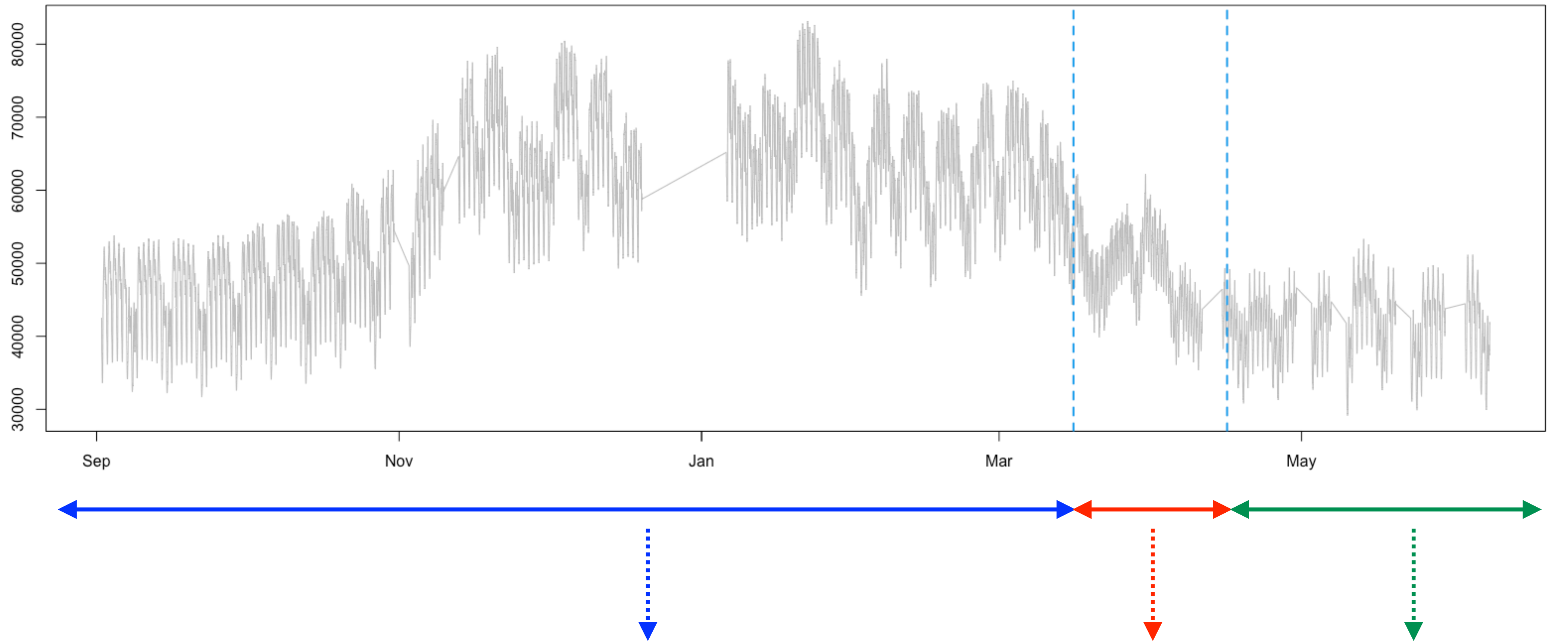
2) Estimation:

$$\hat{\boldsymbol{\theta}}_{t+1} = \hat{\boldsymbol{\theta}}_t + \frac{P_t f(\boldsymbol{x}_t)}{f(\boldsymbol{x}_t)^\top P_t f(\boldsymbol{x}_t) + \sigma^2}\left(y_t - \hat{\boldsymbol{\theta}}_t^\top f(\boldsymbol{x}_t)\right) ,$$
$$P_{t+1} = P_t - \frac{P_t f(\boldsymbol{x}_t) f(\boldsymbol{x}_t)^\top P_t}{f(\boldsymbol{x}_t)^\top P_t f(\boldsymbol{x}_t) + \sigma^2} + Q \,.$$

Q diagonal

- set to 0: *Kalman Static*
- estimated using a greedy algorithm: *Kalman Dynamic*
- reinitialised at the beginning of the lockdown *Break*

- De Vilmarest, J., & Wintenberger, O. (2020)
- See also the today's talk of Joseph de Vilmarest

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De Vilmarest, J., , Obst, D. & Goude, Y. (2020)

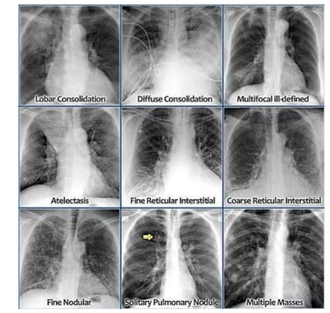
# Transfer Learning

Transfer learning (or learning-to-learn, knowledge transfer, multi-task learning) is a branch of machine learning that aims at reusing knowledge from one source task (usually with a lot of data) on another target one (with few data).

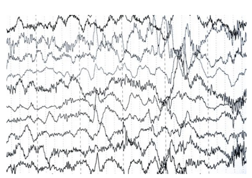
**Source**

**Target**

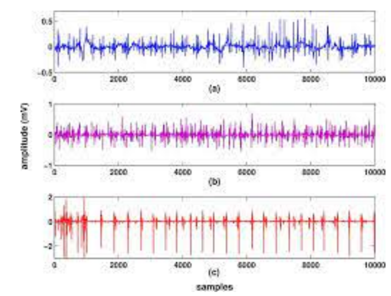
ImageNet



Chestx-ray8



EEG



EMG

Book corpus data

| Label | Sentence | Source |
|---|---|---|
| * | The more books I ask to whom he will give, the more he reads. | Culicover and Jackendoff (1999) |
| ✓ | I said that my father, he was tight as a hoot-owl. | Ross (1967) |
| ✓ | The jeweller inscribed the ring with the name. | Levin (1993) |
| * | many evidence was provided. | Kim and Sells (2008) |
| ✓ | They can sing. | Kim and Sells (2008) |
| ✓ | The men would have been all working. | Baltin (1982) |
| * | Who do you think that will question Seamus first? | Carnie (2013) |
| * | Usually, any lion is majestic. | Dayal (1998) |
| ✓ | The gardener planted roses in the garden. | Miller (2002) |
| ✓ | I wrote Blair a letter, but I tore it up before I sent it. | Rappaport Hovav and Levin (2008) |

Labeled data


- Pan, S. J., & Yang, Q. (2009)
- Bird, J. J., Kobylarz, J., Faria, D. R., Ekárt, A., & Ribeiro, E. P. (2020)
- Radford, A., Narasimhan, K., Salimans, T., & Sutskever, I. (2018)
- Raghu, M., Zhang, C., Kleinberg, J., & Bengio, S. (2019).

# Fine-tuning of GAM

$$y_t = \beta_0 + \sum_{j=1}^{d} f_j(x_{t,j}) + \varepsilon_t$$

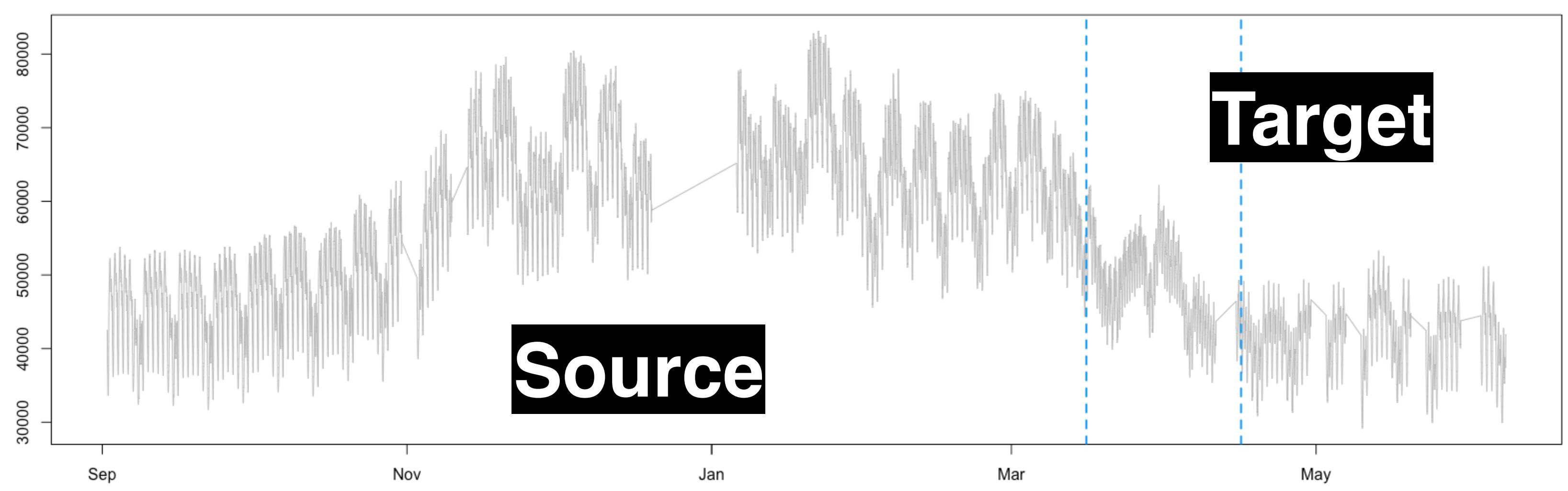
$$f_j(x) = \sum_{k=1}^{m_j} \beta_{j,k} B_{j,k}(x)$$

$$\mathcal{L}_t(\boldsymbol{\beta}) = \sum_{s=1}^{t-1} \Big( y_s - \sum_{j=1}^{d} \sum_{k=1}^{m_j} \beta_{j,k} B_{j,k}(x_{s,j}) \Big)^2$$

**Algorithm 2:** Transfer learning at time step $t$: GAM fine-tuned

**Inputs**: Step size $\alpha$, number of iterations $K$, French source parameters $\hat{\beta}_S^{FR}$

- Initialize $\hat{\beta}_t \leftarrow \hat{\beta}_S^{FR}$.
- Repeat $K$ times:
  $\hat{\beta}_t \leftarrow \hat{\beta}_t - \alpha \nabla \mathcal{L}_{t-1}^{FR}(\hat{\beta}_t)$.
- Predict $\hat{y}_t = \hat{\beta}_t^\top B(x_t)$.



# Transfer Learning from Italian data

Italy was the first country to be massively affected by the COVID 19 in Europe.
The Italian government decreed a total lockdown 7 days before the French one.
The idea is to use this one week head-start to adjust our GAM model for France accordingly to the changes observed in Italy.

We fit a similar GAM on Italian Data, we suppose the variation before/during the lockdown is similar in Italy and France:

Let $\hat{\boldsymbol{\delta}}_t$ be the adjustment done on the Italian GAM coefficients when fine-tuned version on the beginning of march (before the 15th) and $\rho$ a scaling factor between France and Italian data.

$$\tilde{\boldsymbol{\beta}}_t = \hat{\boldsymbol{\beta}}_S^{FR} + \rho\,\hat{\boldsymbol{\delta}}_t \qquad \hat{\rho} = \sum_t y_t^{FR} / \sum_t y_t^{IT}$$

**Algorithm 3:** Transfer learning at time step $t$: GAM-$\delta$

- Initialize $\hat{\beta}_t^{IT} \leftarrow \hat{\beta}_S^{IT}$.
- Repeat $K$ times:
  $\hat{\beta}_t^{IT} \leftarrow \hat{\beta}_t^{IT} - \alpha \nabla \mathcal{L}_{t-1}^{IT}(\hat{\beta}_t^{IT})$.
- Set $\hat{\delta}_t = \hat{\beta}_t^{IT} - \hat{\beta}_S^{IT}$, $\tilde{\beta}_t = \hat{\beta}_S^{FR} + \rho\,\hat{\delta}_t$.
- Predict $\hat{y}_t = \tilde{\beta}_t^\top B(x_t)$.

# Transfer Learning from Italian data+fine-tuning

The advantage of GAM-δ is that it can be applied to reduce the prediction error starting at the very first day of lockdown.

One can afterwards combine this procedure with fine-tuning on the eventually available French data.

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**Algorithm 4:** Transfer learning at time step $t$: GAM-$\delta$ fine-tuned

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- Do fine-tuning on Italian data: $\tilde{\beta}_t = \hat{\beta}_S^{FR} + \rho\,\hat{\delta}_t$.
- Repeat $K$ times:
  $$\tilde{\beta}_t \leftarrow \tilde{\beta}_t - \alpha \nabla \mathcal{L}_{t-1}^{FR}(\tilde{\beta}_t).$$
- Predict $\hat{y}_t = \tilde{\beta}_t^\top B(x_t)$.

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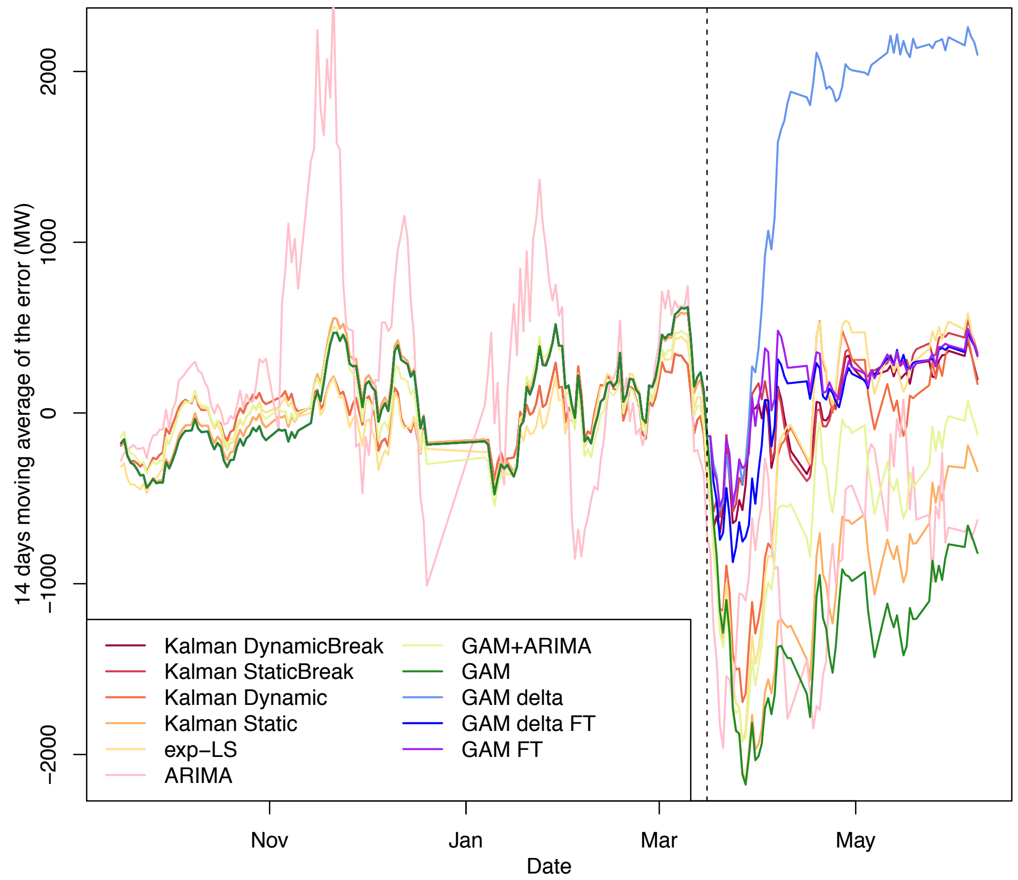


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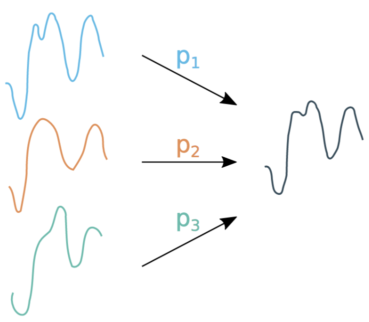
| Fine-tuned | - | 2.78 %, 1917 MW | 1.80 %, 938 MW |
| GAM $\delta$ | - | 4.11 %, 2364 MW | 6.09 %, 2713 MW |
| GAM $\delta$ - Fine-tuned | - | 2.81%, 1912 MW | 1.72 %, 905 MW |

# Online expert aggregation

- We sequentially observe a bounded sequence of observations $y_1, \ldots, y_T \in [0, B]$
- We forecast it step by step and have access at each time *t* to a set of ***experts,*** $x_{1,t}, \ldots, x_{K,t} \in [0, B]^K$
  this experts could be any ML/physical model, human forecasts…
- We then build an aggregation forecast :

$$\widehat{y}_t = \sum_{j=1}^{K} p_{j,t} x_{j,t}$$




- Evaluation of the performances of the individual forecasts and the aggregation is measured with any convex loss e.g. $l_t(x) = (y_t - x)^2$
- The experts and the aggregation are then updated

Cesa-Bianchi, N., & Lugosi, G. (2006)

# Online expert aggregation

- To fix the mind let's consider the simplest algorithm EWA (Exponentially Weighted Aggregation)
- It depends on a single parameter (learning rate) $\eta$ and the weights are updated this way:

$$p_{k,t} = \frac{\exp(-\eta \sum_{s=1}^{t-1} (y_s - x_{k,s})^2)}{\sum_{k=1}^{K} \exp(-\eta \sum_{s=1}^{t-1} (y_s - x_{k,s})^2)}$$

- Vovk, V. G. (1990)
- Warmuth & Littlestone (1994)

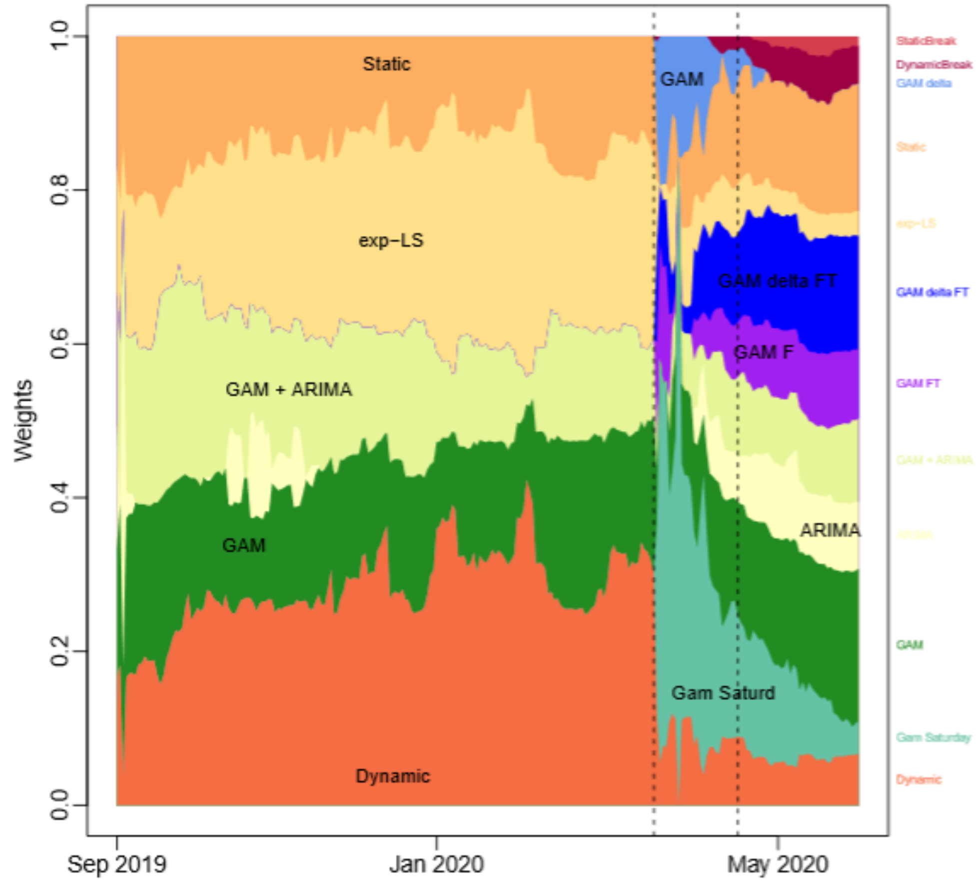
- Oracle bounds of this form can then be obtained

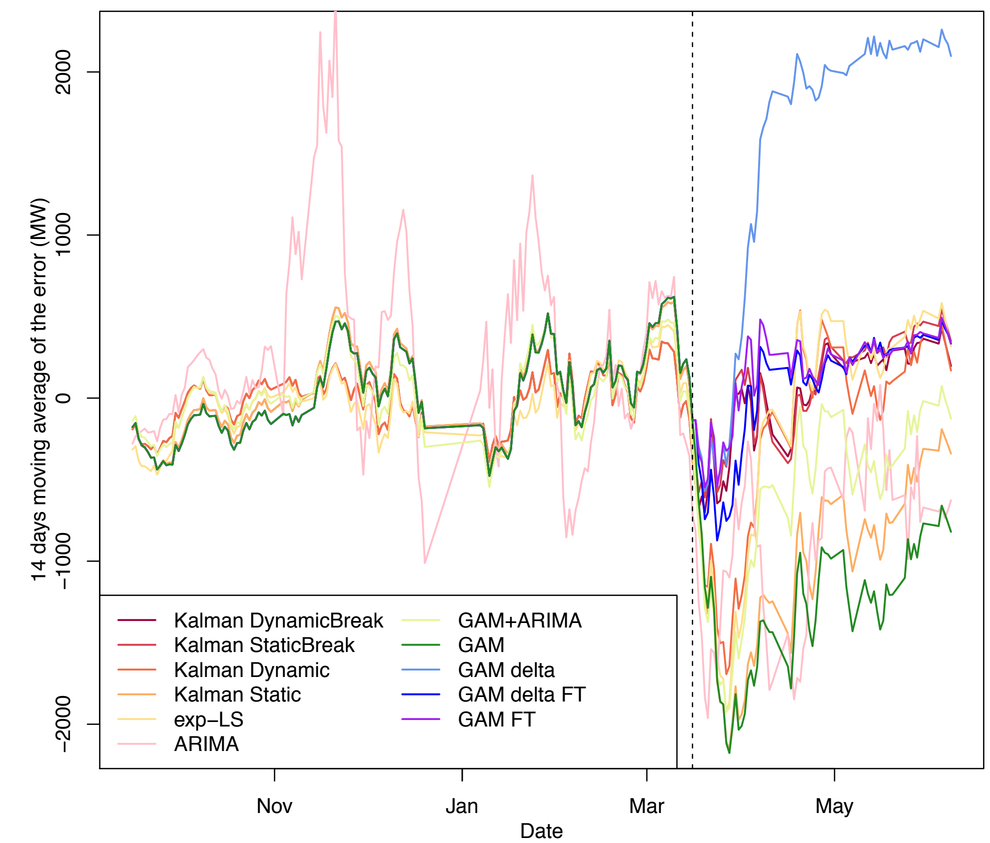
$$\frac{1}{T}\sum_{t=1}^{T}(y_t - \widehat{y}_t)^2 - \min_k \frac{1}{T}\sum_{t=1}^{T}(y_t - x_{k,t})^2 \leq \frac{log(K)}{\eta T} + \eta\frac{B^2}{8} \leq B\sqrt{\frac{log(K)}{T}}$$

$$\eta = \frac{1}{B}\sqrt{\frac{8log(K)}{T}}$$

- A priori information can be added by using sleeping experts: activation or not of an expert at time t

- Wintenberger(2017)
- Gaillard, Stoltz & Van Erven (2014)
- Devaine, M., Gaillard, P., Goude, Y., & Stoltz, G. (2013)

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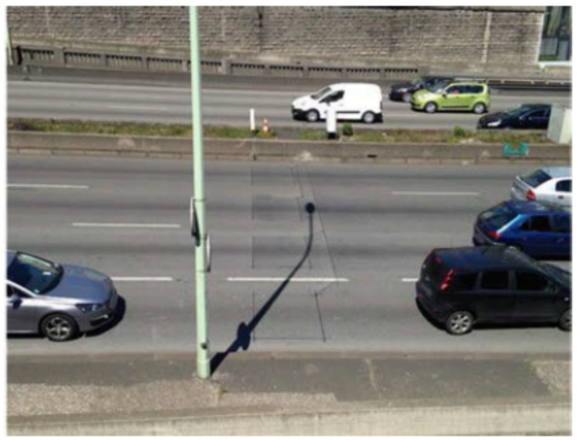
| GAM Saturday | 8.33 %, 6425 MW | 6.09 %, 3970 MW | 8.40 %, 4616 MW |
| Aggregation without GAM Saturday | 1.28 %, 1005 MW | 3.01 %, 2014 MW | **1.44 %, 745 MW** |
| Aggregation with GAM Saturday | 1.28 %, 1005 MW | **2.54 %, 1636 MW** | **1.49 %, 766 MW** |

significant improvement (Diebold-Mariano test) between exp-LS and kalman/fine-tuning approaches also for aggregation over kalman/fine-tuning approaches

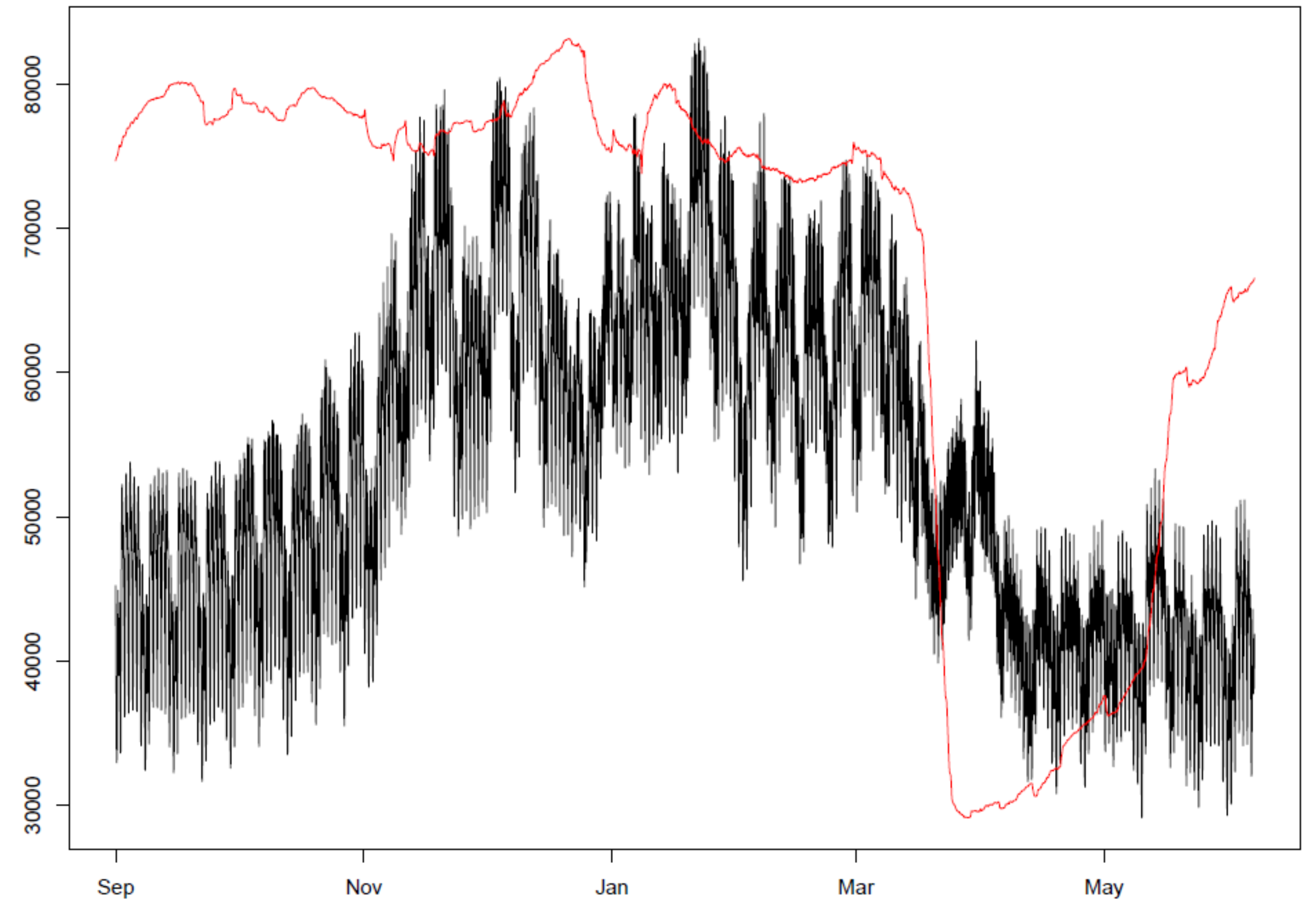
# Complementary Data

# Mobility Data

Traffic Data: https://opendata.paris.fr/



- Occupancy rate
- Traffic flow




GAM with smoothed traffic data improves by 1% (online update) error during lockdown after lockdown the effect of traffic is not consistent.

See also the work of Chen, Y., Yang, W., & Zhang, B. (2020) using mobility data from location app:

https://www.google.com/covid19/mobility/

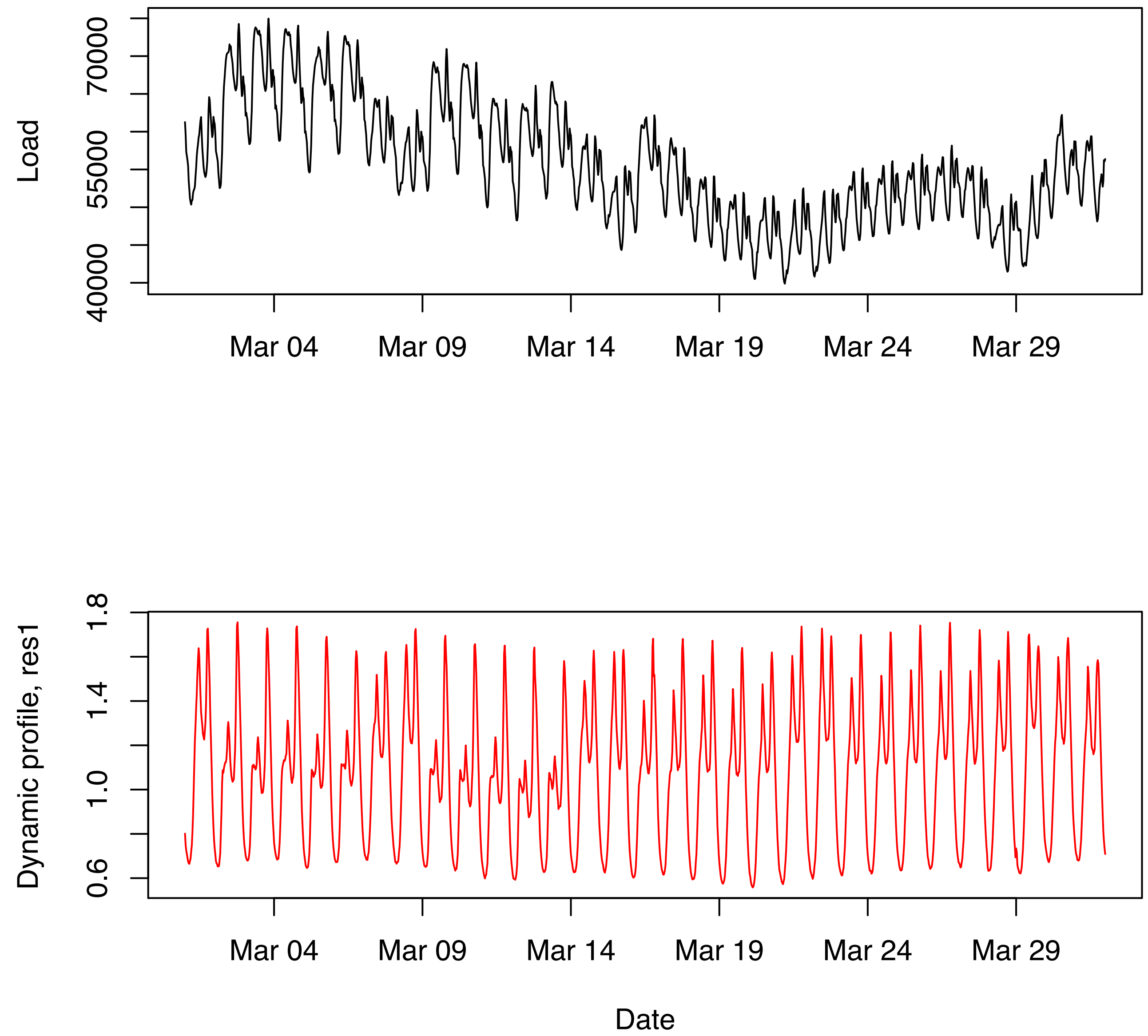
https://www.apple.com/covid19/mobility

They achieve a 4.1% day-ahead forecasting performance during lockdown in France.


- Charansonney, L. (2018)
- Chen, Y., Yang, W., & Zhang, B. (2020)

# Dynamic Panel from Smart Meters

Data published by Enedis (French DSO) since June 2018 https://www.enedis.fr/coefficients-des-profils




Work in progress…

# Conclusions / Perspectives

**We exhibit the consequences of the lockdown on electricity time series forecasting in France**

- Sudden change in level and shape of electricity load.
- Similarities in Italy/France, time shifted

**Related statistical methodes/pbs:**

- Online update: Kalman, aggregation of experts
- Transfer learning

**Open problems/perspectives**

- Enrich with new data from mobility, local/panel data
- Spatio-temporal models to reflect local impact of the pandemic
- Transfer learning with more black box models: RF, deep learning, potentially in high dimension
- Bayesian approach for small historical data (as in Launay, T., Philippe, A., & Lamarche, S. (2015))

- Adjakossa, E, Goude, Y. & Wintenberger, O. (2020) Kalman Recursions Aggregated Online (KAO) https://arxiv.org/abs/2002.12173, submitted to annals of applied statistics.
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# Annexes

# A naïve trick: GAM *Saturday*