Forecasting Net Load in France:
The EDF Data Challenge

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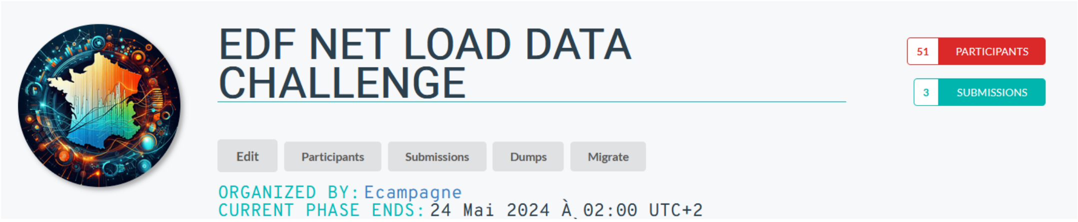
Outline

- Designing a Challenge
- Subject & Data
- Approaches
- Solutions
- Perspectives

Designing a Challenge (1/4)

- « **CodaBench** is an open-source platform for hosting data science challenges, benchmarks and competitions »

Codabench



- **130+ participants** from EDF Group in 46 teams, on **virtual machines** provided by EDF
- Starting kits and GPU available
- **Animate a data-science community** at EDF, get people working on a **subject of interest**

Designing a Challenge (2/4)

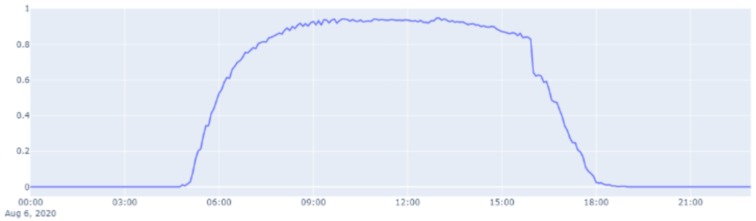
Motivations

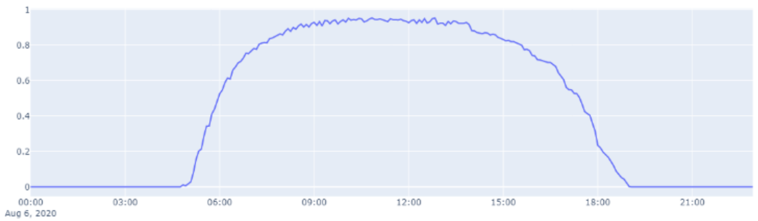
- Maintaining a **balance between electricity supply and demand** is important for **grid stability**
- Providing **accurate forecasts** for short-term electricity load is therefore crucial for all participants in the energy market
- The availability of new **geolocalized data and individual electricity consumption data** can be exploited by models that are able to take advantage of additional information and help in **minimizing forecast error**

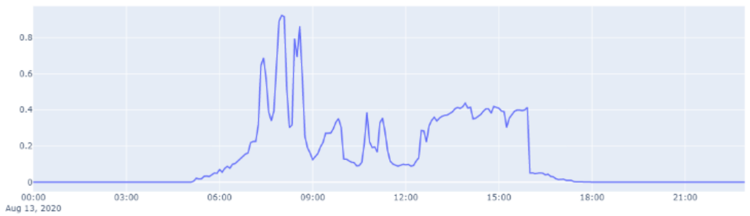
Designing a Challenge (3/4)

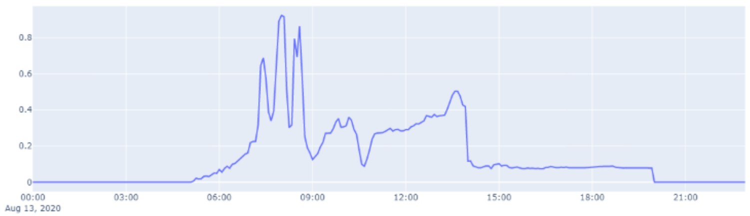
- The increasing contribution of **renewable energy sources brings fluctuations and intermittency** to the electricity market

  ➢ Complex representation of meteorological variables such as clouds



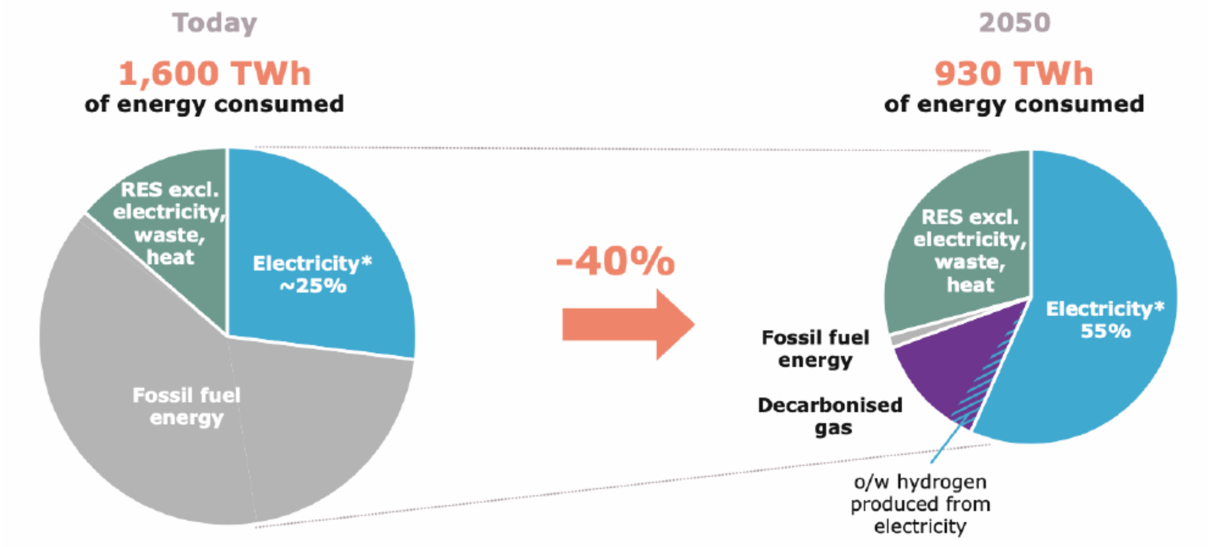


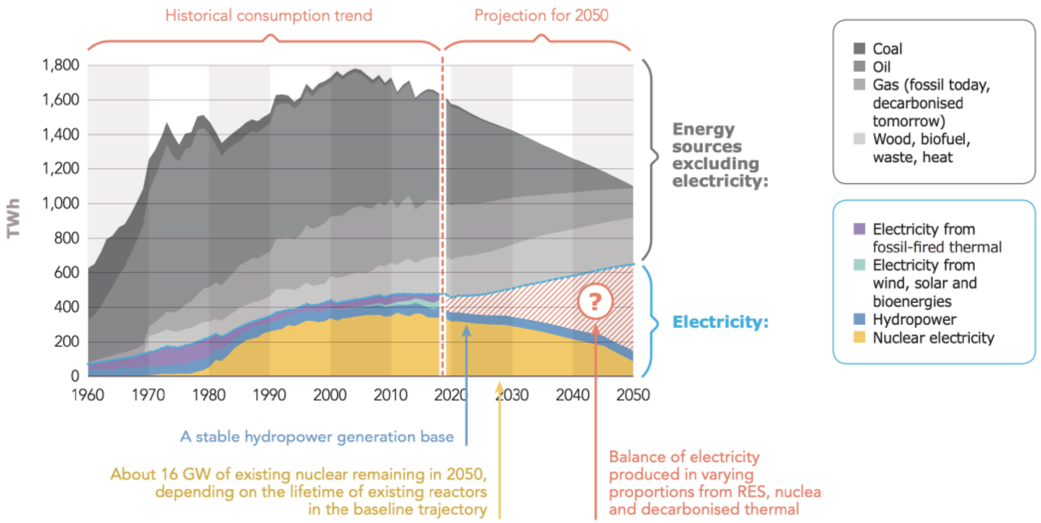




  ➢ Installed capacity is not precisely known and production measures are imperfect

Designing a Challenge (4/4)





Subject & Data (1/3)

Objective

- Develop methods that can take into account regional data to forecast **daily minimum and maximum net load* over France**

Perimeter

- Mainland France (excluding Corsica)

Challenges

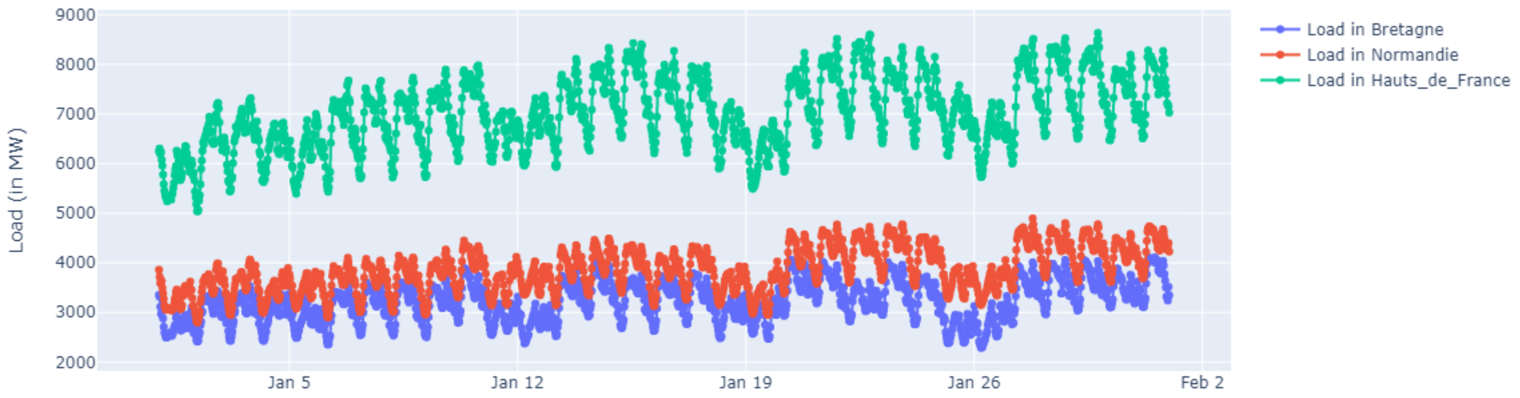
- Model renewable electricity production as accurately as possible
- Use data at different scales: regional and national

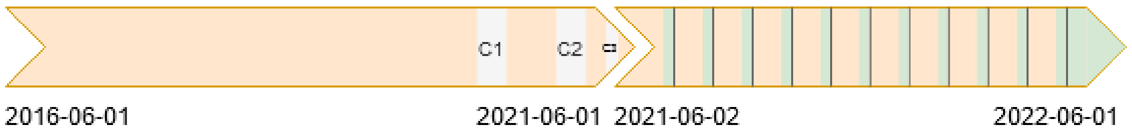
*Note that net load is defined as the difference between demand and renewable generation.

Subject & Data (2/3)

3 datasets: regional, national and price

- 12 administrative regions of France are considered
- 32 weather stations (appearing as black dots)
- Half-hourly data

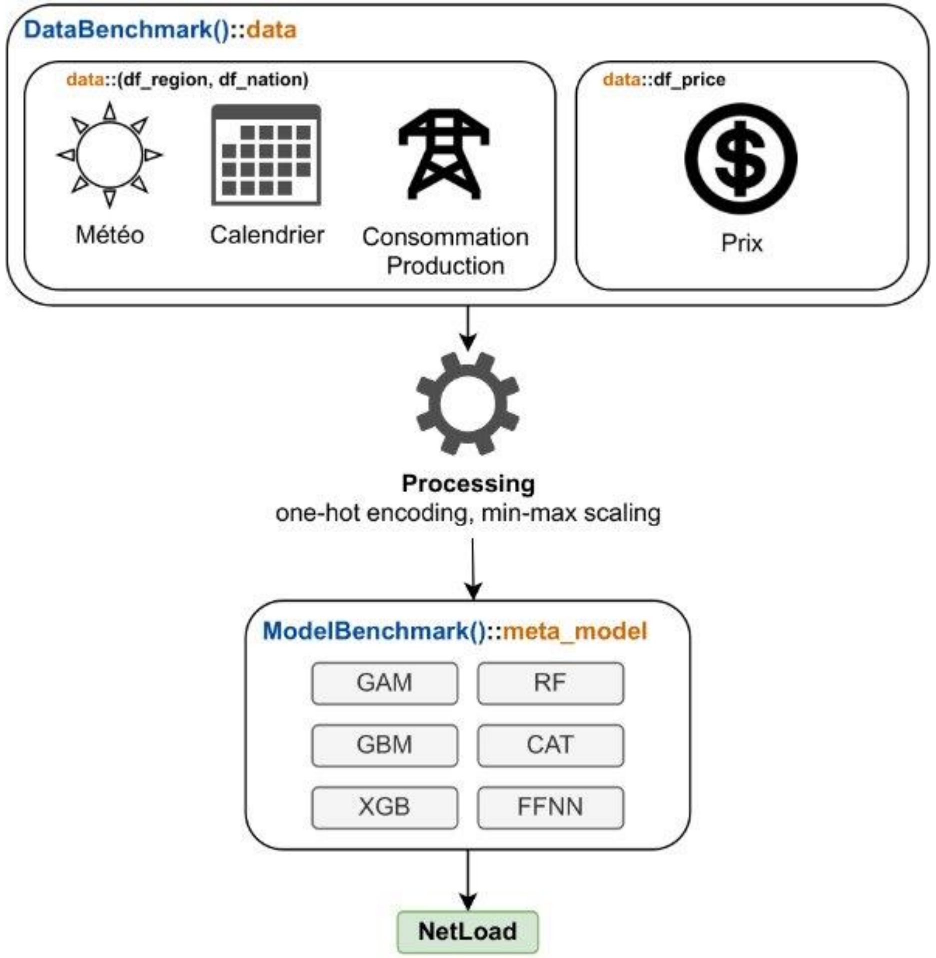




Training and test periods

- Train = orange, test = green
- Test period = last week of each month + May 2022
- Covid containment periods (grey) have been invalidated

Subject & Data (3/3)



Features

- Climatic, calendar and load data
- Spot price of electricity

Processing

- One-hot encoding
- Min-max scaling per region

Approaches

Geolocalized Data

- A natural approach consists in **predicting the national net load using national data**
- However, some **regions do not behave in the same way (weather, economy,…)** which can be hidden in a national forecast
- Aggregation of the regional forecasts can be done with a simple sum, but there are connexion problems

Net Load, Load – Production, Load – (Solar Power + Wind Power)?

- In practice, predicting all the **individual components give better results**

Mean predictions or Extreme predictions?

- **Small or large resolution**: predicting the mean and then taking the extremes or directly predicting the extremes (Scaled Student, Generalized Extreme Value Distribution,…)?
- Number of data points is reduced when directly trying to predict the extremes
- Best approach is to consider a multi-resolution prediction: **Amara-Ouali, Y., Fasiolo, M., Goude, Y., & Yan, H. (2022). Daily peak electrical load forecasting with a multi-resolution approach. International Journal of Forecasting**

Solutions (1/3)

Evaluation

- Participants were evaluated using the following loss:

$$\ell(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{d=1}^{n}\left(\min y_{48d:48(d+1)} - \min \hat{y}_{48d:48(d+1)}\right)^2} + \sqrt{\frac{1}{n}\sum_{d=1}^{n}\left(\max y_{48d:48(d+1)} - \max \hat{y}_{48d:48(d+1)}\right)^2}$$

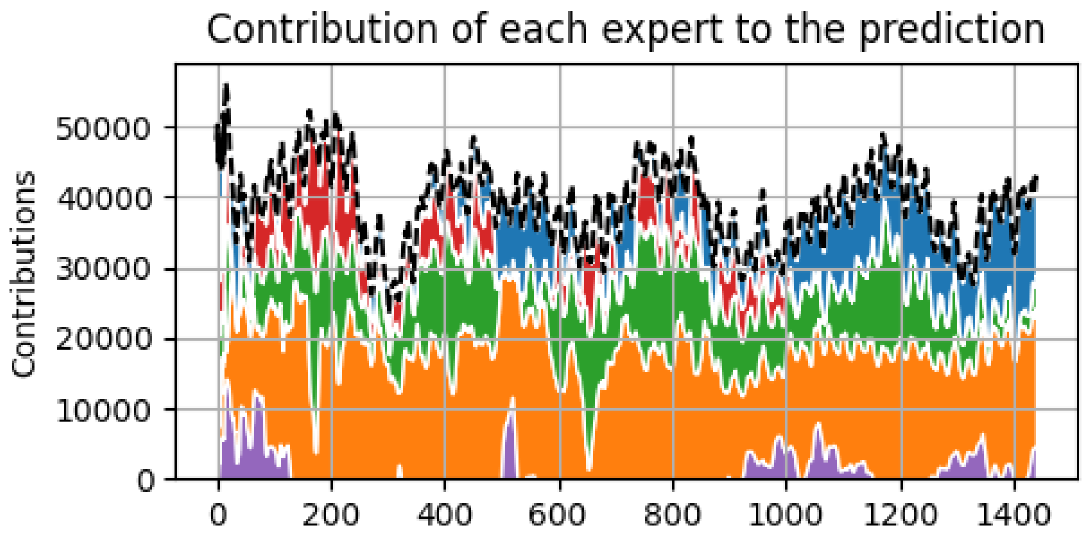
- The loss function is **the sum of the RMSE on the min and the max predictions** of all days (a day = **48 instants**)

Benchmark models

Participants were competing against basic benchmark models (trained on the RMSE of the mean predictions) to help them evaluate the quality of their own models:

- **GAM-1**: a GAM (Generalized Additive Model) forecasting the **net load**
- **GAM-3**: a GAM forecasting the **load**, the **wind production** and the **solar production**
- **CAT & xGB**: a CatBoost model & a xGBoost model
- **FF:** a Feed-Forward neural network model
- **Mixture**: a mixture of the above models

Solutions (2/3)



Benchmark models

- In average, **GAMs are the best performing** individual experts
- **ML-Poly aggregation outperform** the individual estimators on both the **validation and test sets** (except for GAM-3)
- Weights are **optimized on a validation set** and then **frozen for the test set**

Model	Loss (MW) Public Test	**Loss (MW) Private Test**	Loss (MW) Average Test
GAM-1	6226	8304	7265
GAM-3	**3946**	**4929**	**4438**
xGB	14364	14383	14374
CAT	18969	19569	19269
FF	14824	13342	14083
Aggregation ML-Poly	*4805*	*5091*	*4948*
Aggregation Uniform	9200	8823	9012

Solutions (3/3)

Participants models

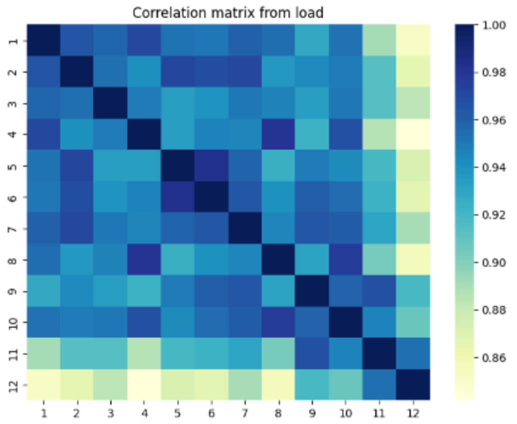
- **14 teams**/46 did a better score than the baseline on the private test set
- The best solutions **compute new features**, perform a **cross validation with multiple models** while **tuning their hyperparameters**, and select the **best model in average** on the folds
- The Final Strike used a **Light Gradient Boosting Machine Regressor (LGBMR)**
- Les Equilibristes used **two xGB models**, one for the load, and one for the production
- The Data Rangers aggregated a **GAM per instant** (7%), an **xGB** model (80%) and a **Bidirectional Recurrent Neural Network per instant** (**BRNN**, 13%)

Rank	Teams	Model	Loss (MW) Public Test	**Loss (MW) Private Test**	Loss (MW) Average Test
1	**Final Strike**	**LGBMR**	**2580**	**2747**	**2664**
2	*Les Equilibristes*	*xGB*	3352	*3040*	3196
3	Data Rangers	Mixture	2994	3098	*3046*
4	Les Green Code	xGB	3153	3172	3163
5	Les Syracusains	GAM	*2845*	3257	3051
6	Kung Fu Pandas 2	Mixture	3093	3370	3231
7	SoDataSum	GAM	3251	3442	3347
…	…		…	…	…
15	Baseline	GAM-3	3946	4929	4438

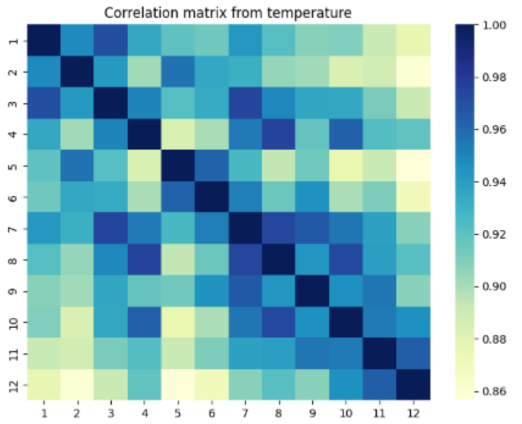
Perspectives (1/3)

Graph Neural Networks

- **CIFRE thesis** between EDF and Centre Borelli (Y. Amara-Ouali, A. Kalogeratos, M. Mougeot)
- GNNs can **handle spatial data using graph structures**
- We want to make use of the deep relationships that exist between the regions as their **features are strongly correlated**
- GNNs effectively **compute representations through convolutions** using the relationships within the data:
  - **Spatial** convolutions (adjacency matrix)
  - **Spectral** convolutions (Laplacian matrix)



(a) Correlation matrix obtained from consumption data.



(b) Correlation matrix obtained from temperature data.

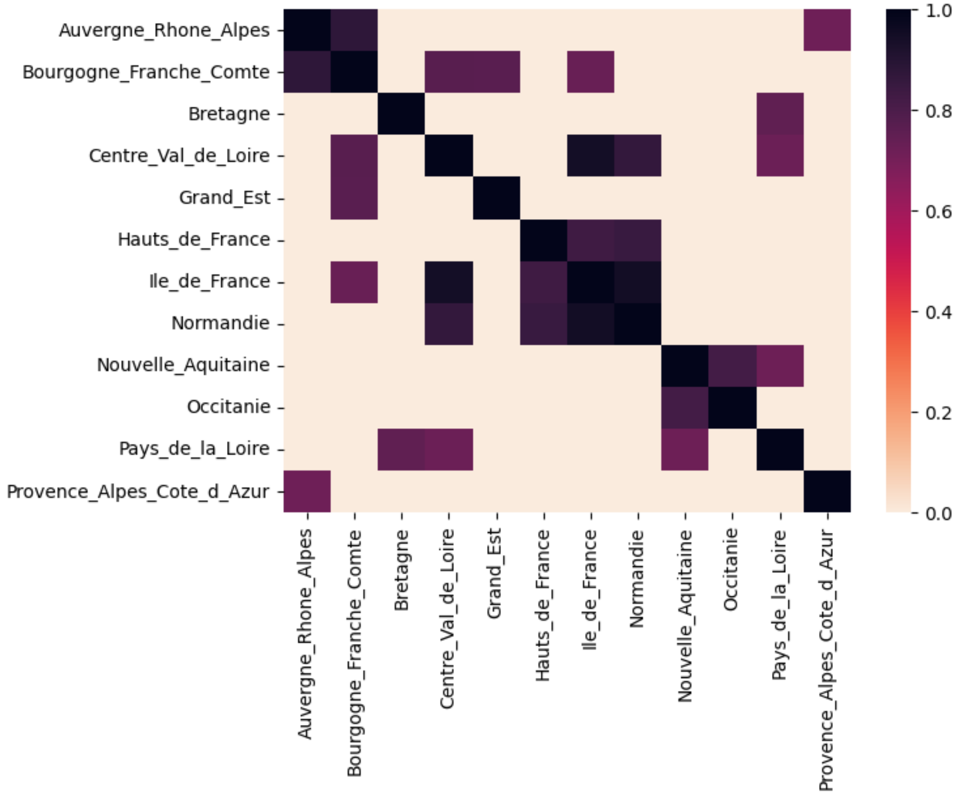
$$h_v^{(0)} = X_v,$$
$$h_v^{(k)} = \mathbf{UPDATE}^{(k)}\left(h_v^{(k-1)}; \mathbf{AGGREGATE}^{(k)}\left(\left\{h_u^{(k-1)} \mid u \in \mathcal{N}_v\right\}\right)\right)$$

Spatial

$$h^{(0)} = X,$$
$$h^{(k)} = \sigma\left(g_\theta \star_G h^{(k-1)}\right) = \sigma\left(g_\theta(\mathbf{L})h^{(k-1)}\right) = \sigma\left(\sum_{\ell=0}^{N-1} \theta_\ell \mathbf{L}^\ell h^{(k-1)}\right)$$

Spectral

Perspectives (2/3)



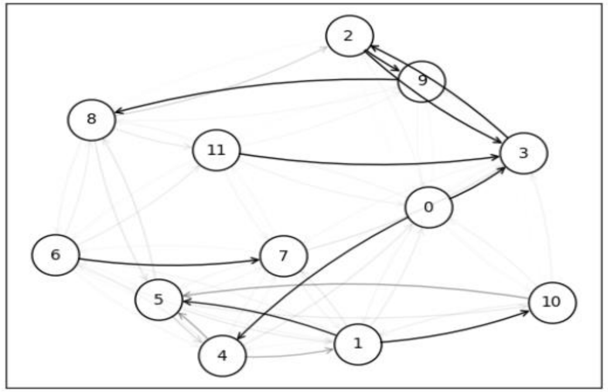
Graph structures

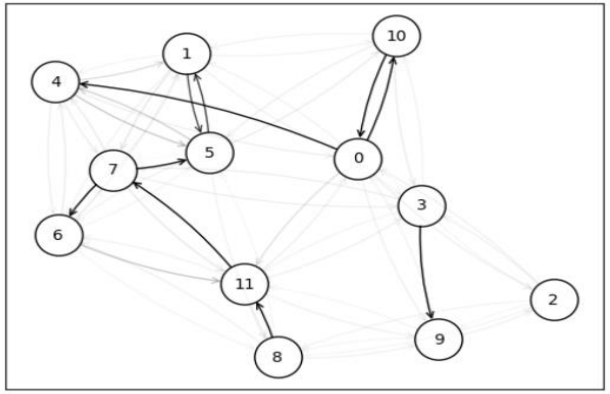
- **Statistics oriented**: correlation and precision matrices
- **Distance oriented**: DTW and Exponential similarity matrices
- **Time dependent structures**

Explainability

- Making **explainable forecasts** is a crucial point for EDF, GAM models **give both good results and interpretable forecasts**
- GNNs can highlight links between nodes and **therefore important subgraphs can be extracted**:

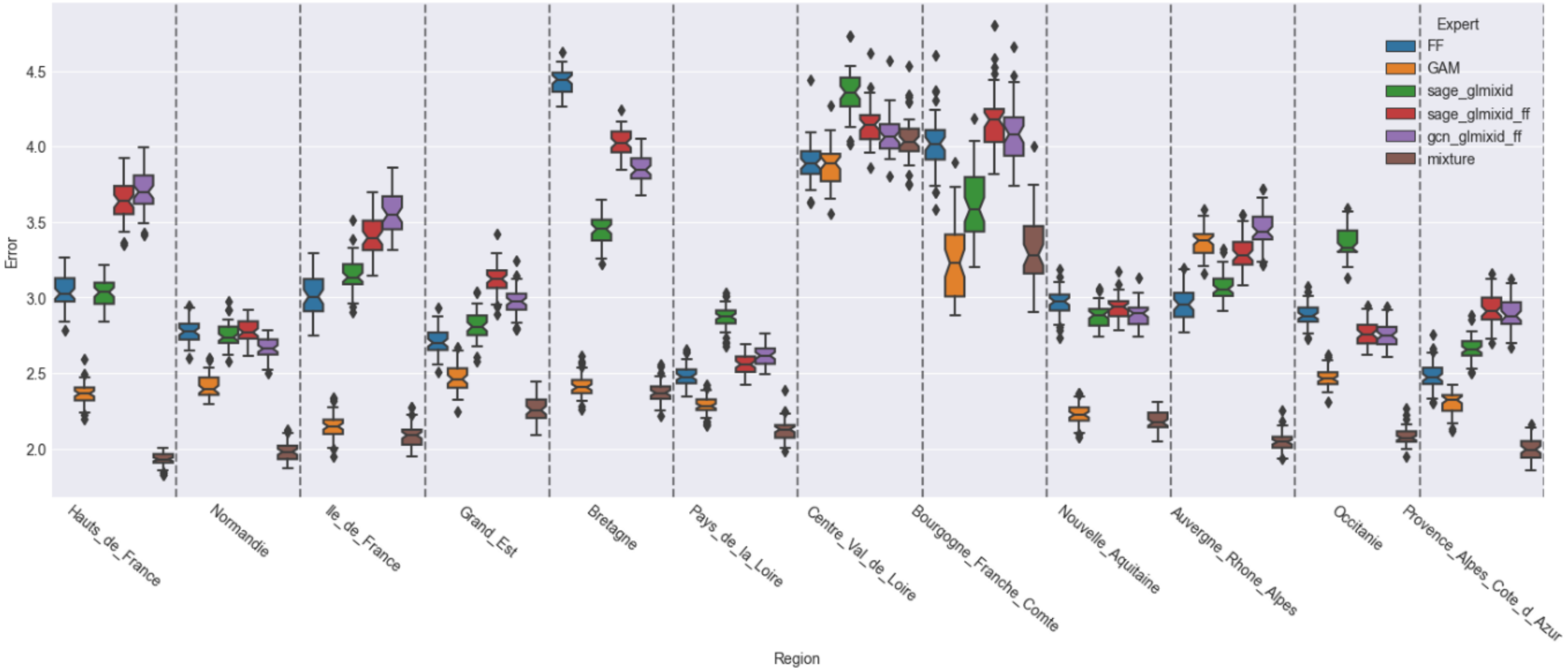
$$\max_{G_S} \mathbf{MI}(Y_G, G_S) \stackrel{\text{def}}{=} H(Y_G) - H(Y_G \mid G = G_S,\ X = X_S)$$





Perspectives (3/3)

- **Promising results** on the load



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Thank you!

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Annexes (1/3)

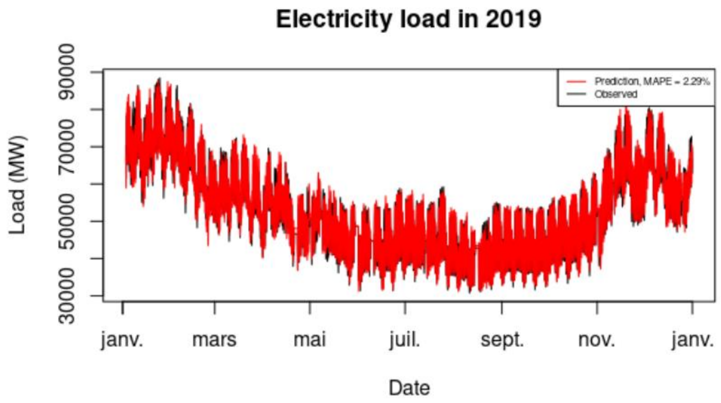
Generalized Additive Models

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

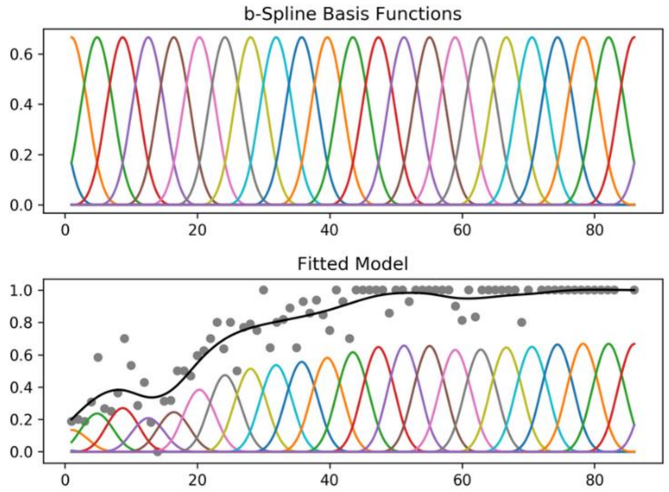
where β_0 is the intercept, $X_t = [x_{t,1}, \ldots, x_{t,d}]$ and (ε_t) is an i.i.d. random noise.

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

with coefficient $\mathbf{B_j} \in \mathbb{R}^{m_j}$ where m_j is the chosen spline basis dimension



(a) Load prediction for 2019 using GAM.



(b) A GAM model and its spline basis.

Annexes (2/3)

Boosting Models

- Class of machine-learning models that **combine sequentially weak learners** (e.g. decision trees) building a complex regression model,

- Each new simple model added to the ensemble **compensates for the weaknesses** of the current ensemble,

- **CatBoost** is usually chosen for its **fast optimization** and ability to handle **categorical variables** data (especially calendar data),

Annexes (3/3)

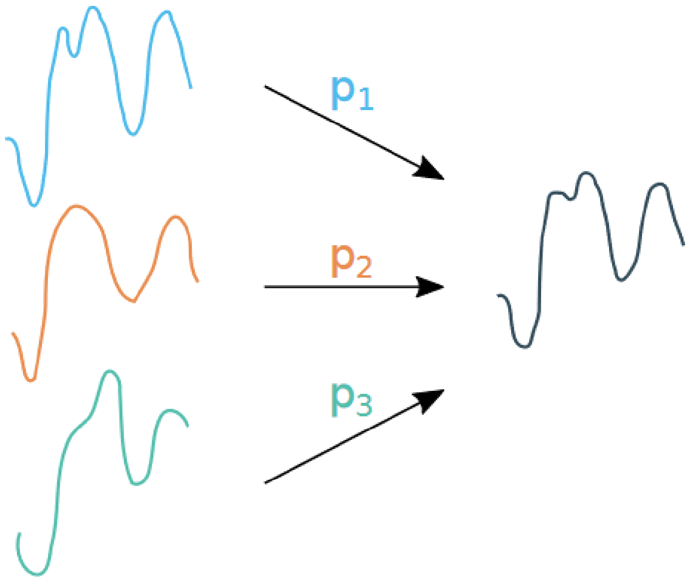
Aggregation of Experts

- Exponentially Weighted Average (EWA)

$$\widehat{p}_{k,t} = \frac{e^{-\eta \sum_{s=1}^{t-1} \ell_s(x_{k,s})}}{\sum_{i=1}^{K} e^{-\eta \sum_{s=1}^{t-1} \ell_s(x_{i,s})}}$$

- Polynomial weighted averages with multiple learning rates (ML-Poly)

  - set $\eta > 0$
  - set initial weights to $p_{j,1} = 1/N$
  - initialize $\widehat{y}_1 = \sum_{j=1}^{N} p_{j,1} f_{j,1}$
  - for $t = 2, \ldots, T$
    - for each expert j, pick the learning rates: $\eta_{j,t-1} = 1/\left(1 + \sum_{s=1}^{t-1} (l(\widehat{y}_s, y_s) - l(f_{j,s}, y_s))^2\right)$
    - update the weights: $p_{j,t} = \eta_{j,t-1} \frac{R_t(\delta_j)^+}{R_t(MLpol)^+}$
    - then aggregation: $\widehat{y}_t = \sum_{j=1}^{N} p_{j,t} f_{j,t}$



$$\hat{y}_t = \sum_k p_{k,t} x_{k,t}$$