

Statistical and Sequential Learning for Time Series Forecasting

Introduction

Margaux Brégère

Course syllabus

Framework

Schedule

Evaluation

Use case: forecasting french electricity consumption

Challenges

Data

Descriptive analysis

Course syllabus

Time series forecasting framework

Let $Y = (Y_t)_{t \in \mathbb{N}^*}$ be a discrete time processes where t refers to time and Y_t is a random variable

Assumption: at a time step $t = 1, 2, 3, \dots$

- Observe the data with a delay $d: Y_1, Y_2, ..., Y_{t-d}$
- Observe potentially random explanatory variables $X_t \in \mathbb{R}^p$ not restrictive since a categorial variable with m categories may be encoded in $\{1, ..., m\}$ or $\{0,1\}^m$

Aim

Providing forecasts $\hat{Y}_t, ..., \hat{Y}_{t+h}$ of the future realisations of Y at a horizon $h \in \mathbb{N}$ \mathbb{C} Model $\hat{f}_t^h: \left(t, Y_1, Y_2, ..., Y_{t-d}, X_t\right) \mapsto \hat{Y}_{t+h}$ trained on $\left\{Y_s, X_s\right\}_{s=1,...,t-d}$

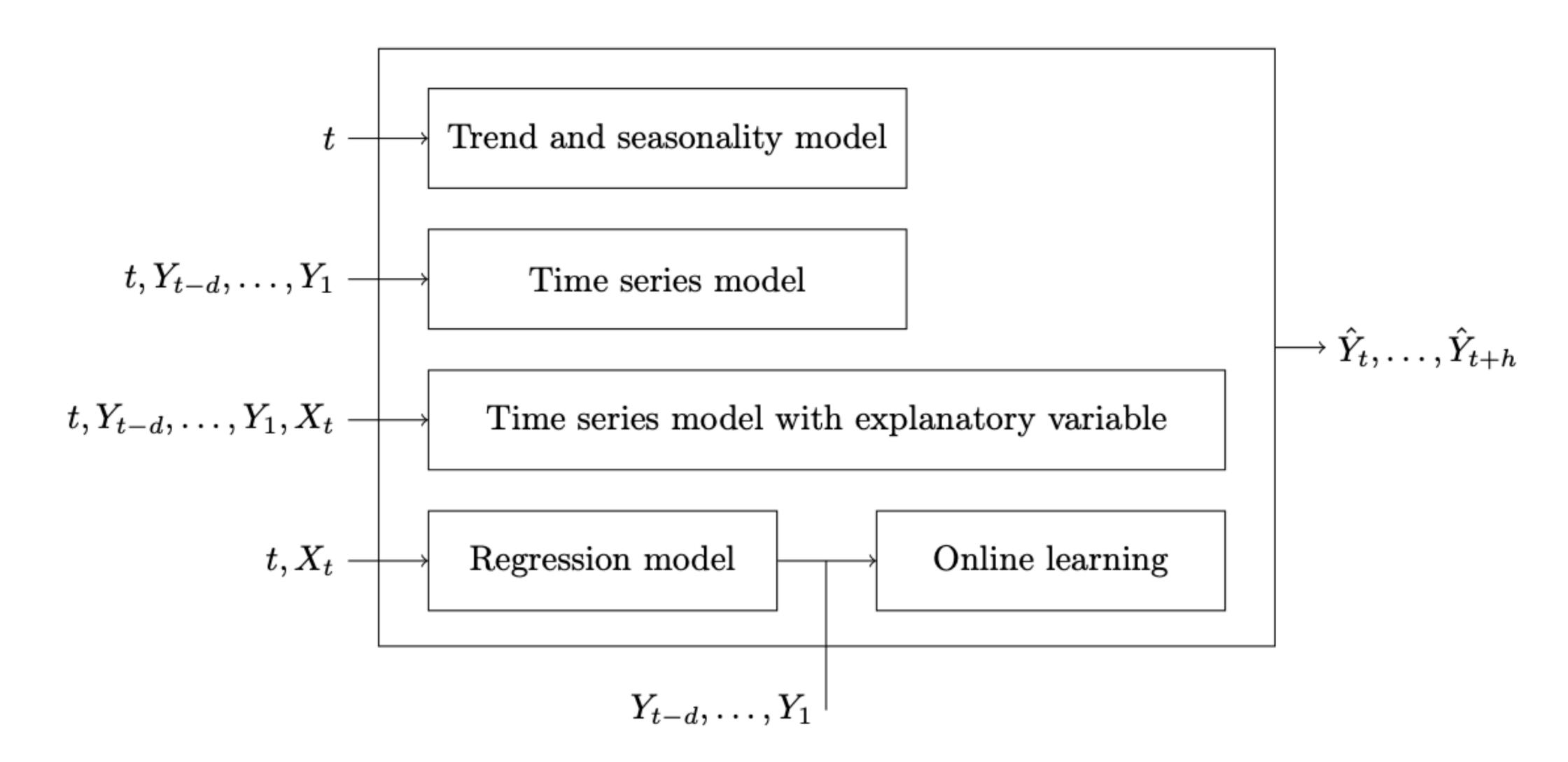
Forecast evaluation:

On a testing dataset $\left\{Y_s,X_s\right\}_{s=T_1,\,...,\,T_n}$ and a loss function \mathscr{C} , we aim to minimise $\frac{1}{n}\sum_{s=T_1}^{T_n}\mathscr{C}\big(Y_{s+h},\hat{Y}_{s+h}\big)$

Time series forecasting framework

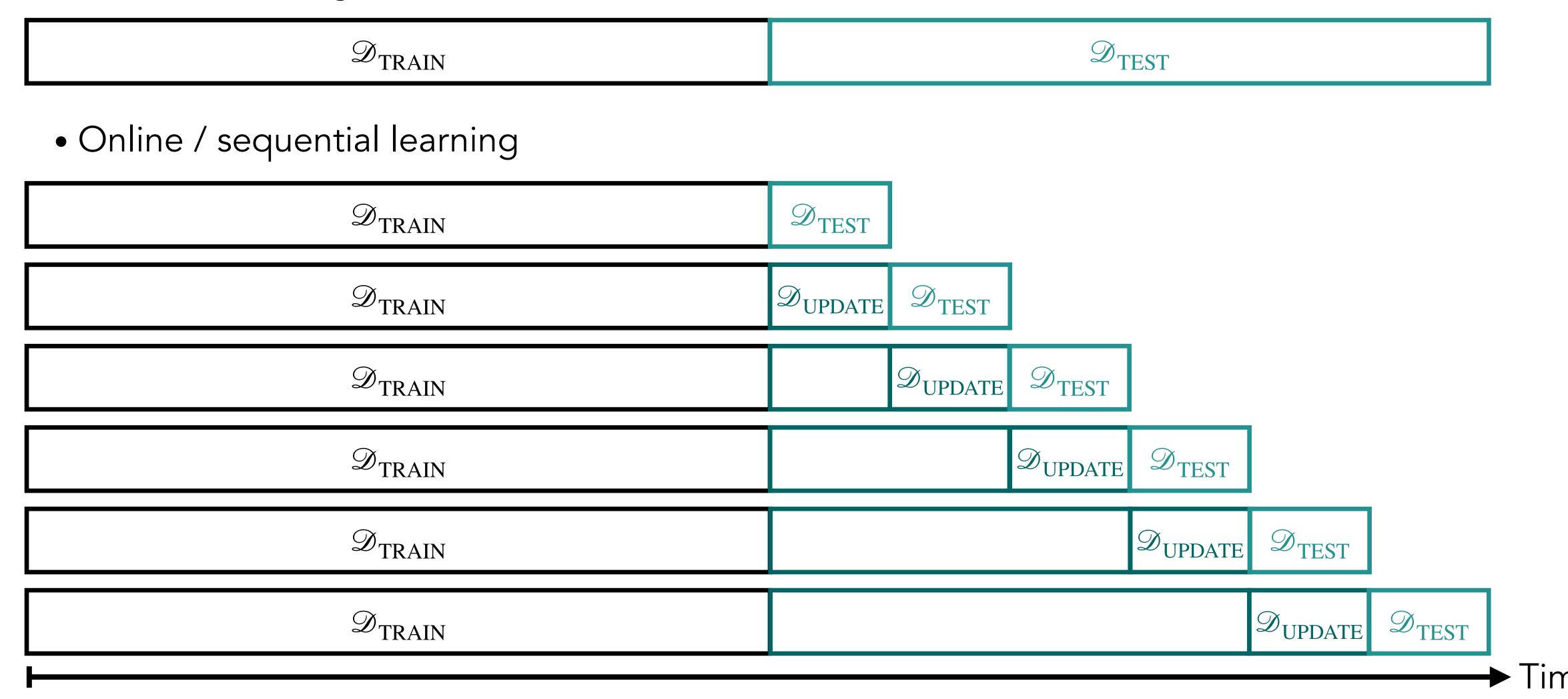
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Supervised (target Y_t)
Sequential (\hat{f}_{t+1}^h \neq \hat{f}_t^h) learning for Regression (Y_t \in \mathbb{R})
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Time series forecasting



Time series forecasting

Classical learning



Objectives

- Understand the challenges involved in forecasting time series:
 Mean forecast, probabilistic forecast, quantiles, extremes, simulation
 Online learning (adaptive models, transfer learning, expert aggregation)
- Present various statistical and learning methods (linear, random forests, bagging, boosting, neural networks, etc.)
- Implement these methods in R and/or Python as the course progresses

Schedule

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Oct. 23, 2023 09h00 - 12h15 + 17h00 - 18h30 • Introduction, Times series analysis
Oct. 25, 2023 13h30 - 16h45 • Penalised Regression, Online approaches
Nov. 06, 2023 09h00 - 12h15 + 17h00 - 18h30 • Generalised Additives Models, Online approaches
Nov. 08, 2023 13h30 - 16h45 • Random Forest and Boosting, Online approaches
Nov. 15, 2023 13h30 - 16h45 • Project session
Nov. 20, 2023 09h00 - 12h15 • Recurrent Neural Networks and variations
Nov. 22, 2023 13h30 - 16h45 • Online expert aggregations
Nov. 29, 2023 13h30 - 16h45 • Interpretability
Dec. 06, 2023 13h30 - 16h45 • Project session
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Dec. 13, 2023 13h30 - 16h45 • Opening: probabilistic forecasting and generative models

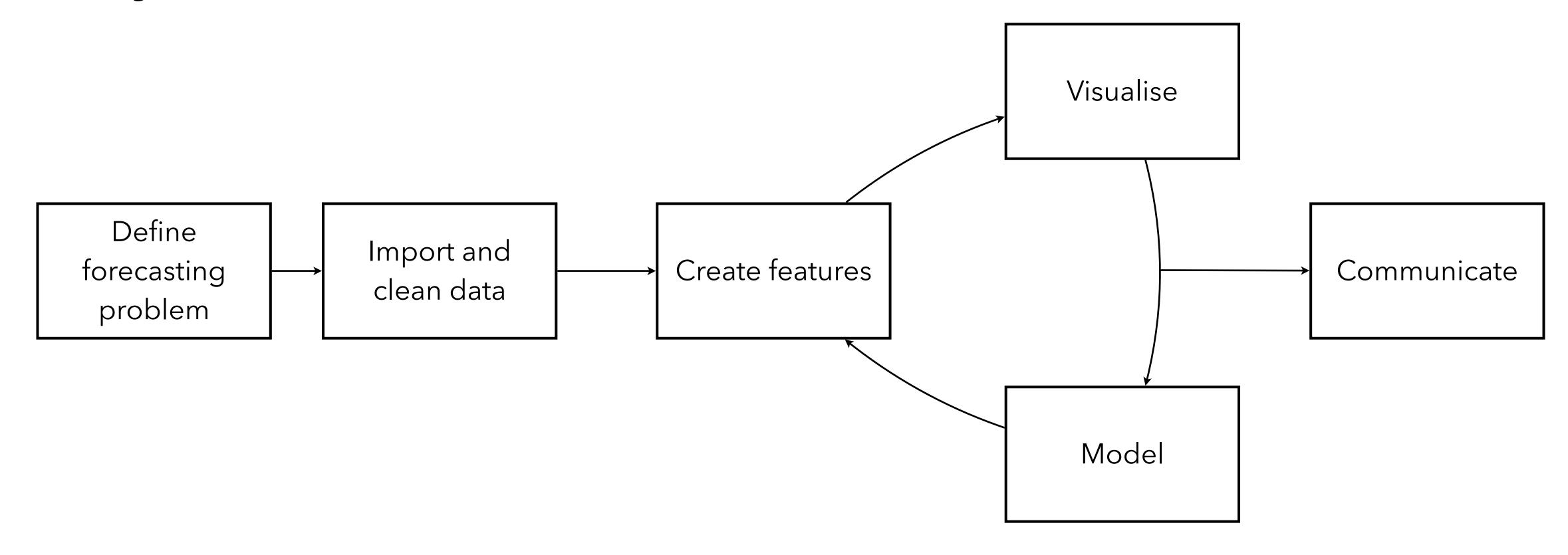
Evaluation - Project timeline

- Constitute pairs or trios
- Choose a dataset (data.gouv.fr, kaggle.com/datasets, data.oecd.org, etc.)

A single requirement: the variable of interest must be a time series!

- Define our forecasting problem (motivation, delay, horizon)
 - ✓ You need my approval to continue
- Define benchmark forecasts (persistent model, existing predictor)
- Define a testing methodology
- Work: impute missing data, design features, model, visualise, tune to beat the benchmark
- Do not forget sequential aspect (online learning)
- Provide reproductible results, analyse

Project



« All models are wrong, but some are useful » George Box

Objectives

Handle real data

Pose a forecasting problem

Understand statistical and online learning methods and their implementation (R or python)

Work in pairs/trios and use collaborative tools (Git)

Build and validate a predictive model

Present results orally and in writing

Provide reproducible code

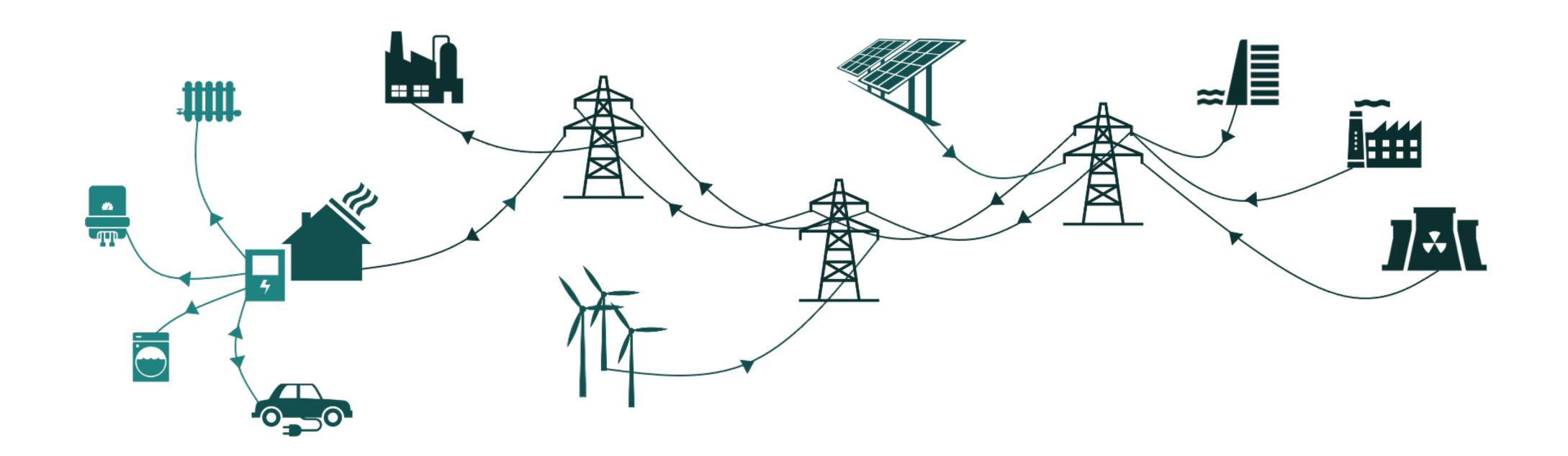
Yardstick of the evaluation

- 1 point Literature review
- 2 points Data processing (imputation of missing data, feature engineering)
- 1 point Descriptive analysis
- 5 points Modelling and validation of final model (test methodology)
- 2 points Analysis of results (bias, variance, etc.)
- 2 points Code (comments, reproducibility, effectiveness)
- 3 points Report
- 4 points Oral presentation (fluency and clarity, motivation, pedagogy, answers to questions)

Use case: forecasting french electricity consumption



Challenges



As electricity is hard to store, balance between production and demand must be strictly maintained

Forecast demand and adapt production accordingly

From short to long-term

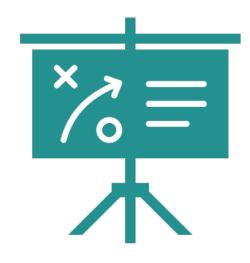
Short term (from a few hours to two weeks)
 Scheduling and optimising the use of power plants
 Avoiding black outs
 Reducing rebalance coasts



Mid term (from two weeks to five years)
 Planning power plant maintenance episodes.



Long term (from five to fifty years)
 Providing prospects for the evolution of the customer portfolio
 Adapting commercial offers accordingly
 Defining an investment strategy



From dis-aggregated to aggregated level



Dis-aggregated level

Modelling new electrical uses (auto-consumption, electrical vehicles)

Designing demande response solutions

 \triangle Smart meters data is highly sensitive and erratic \bigcirc simulation models



Neighbourhood / city level

Managing networks locally (Smart Grids)

Dispatching electricity at junctions between transport (high-voltage lines) and distribution (medium- and low-voltage lines) networks



National level

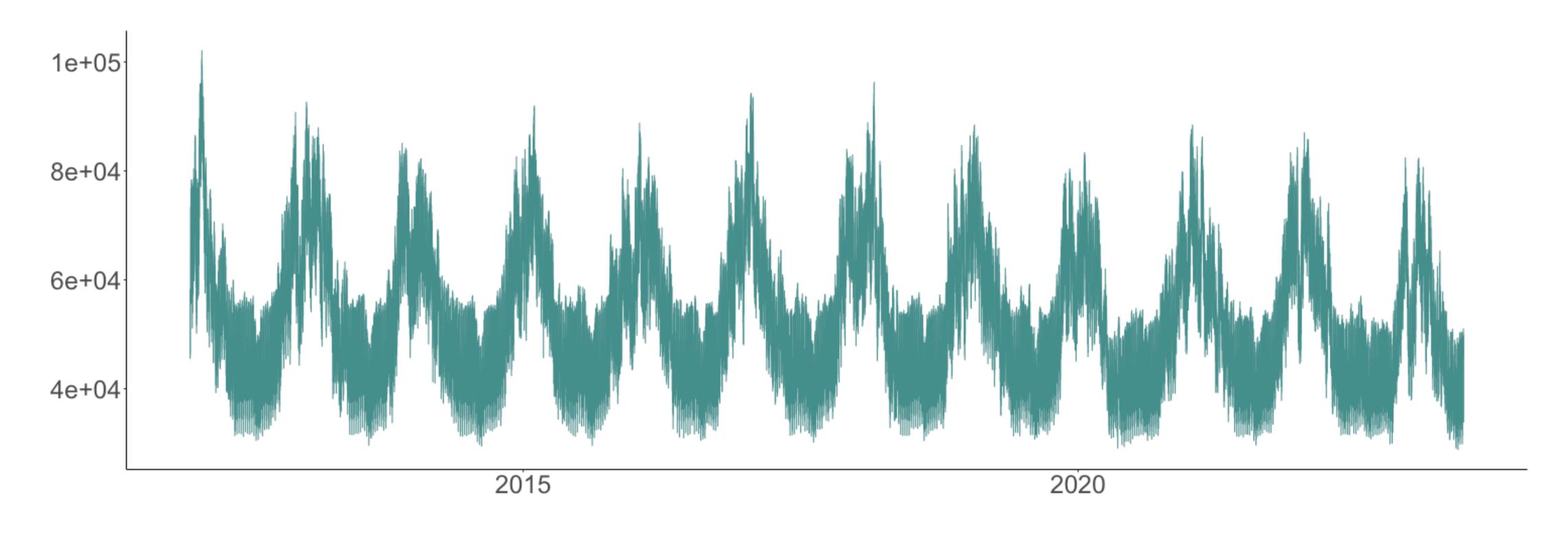
Managing the overall balance

Planning cross-border exchanges

Growing area of research: forecast reconciliation

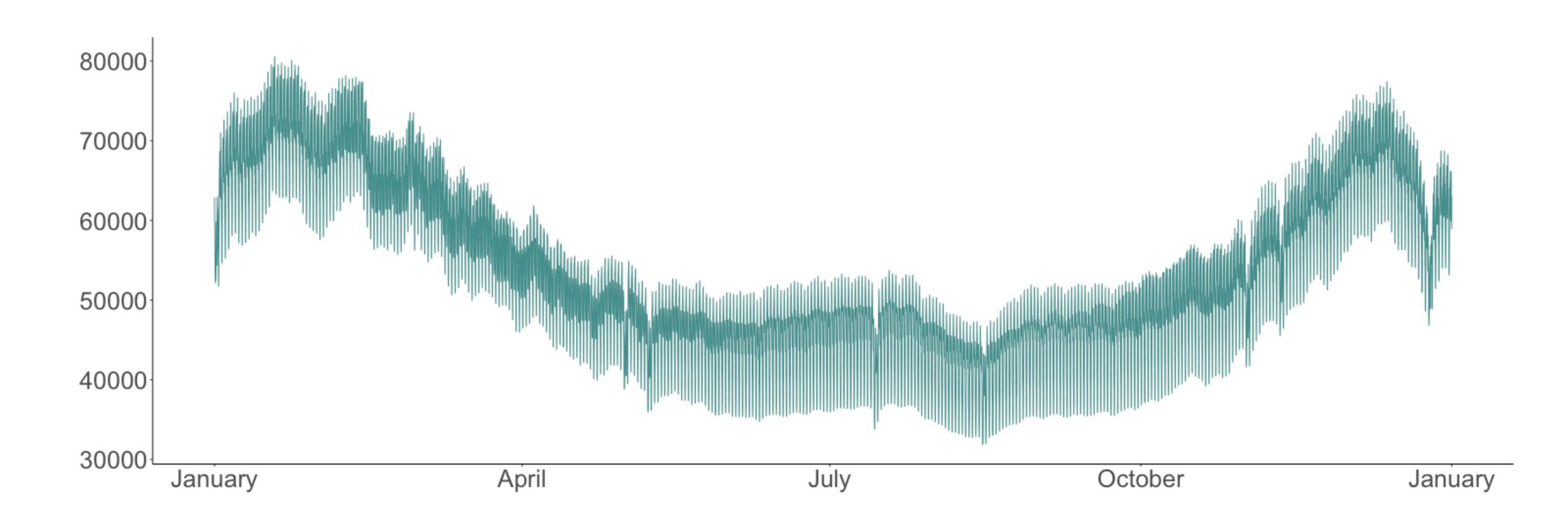
Data

https://www.rte-france.com/eco2mix

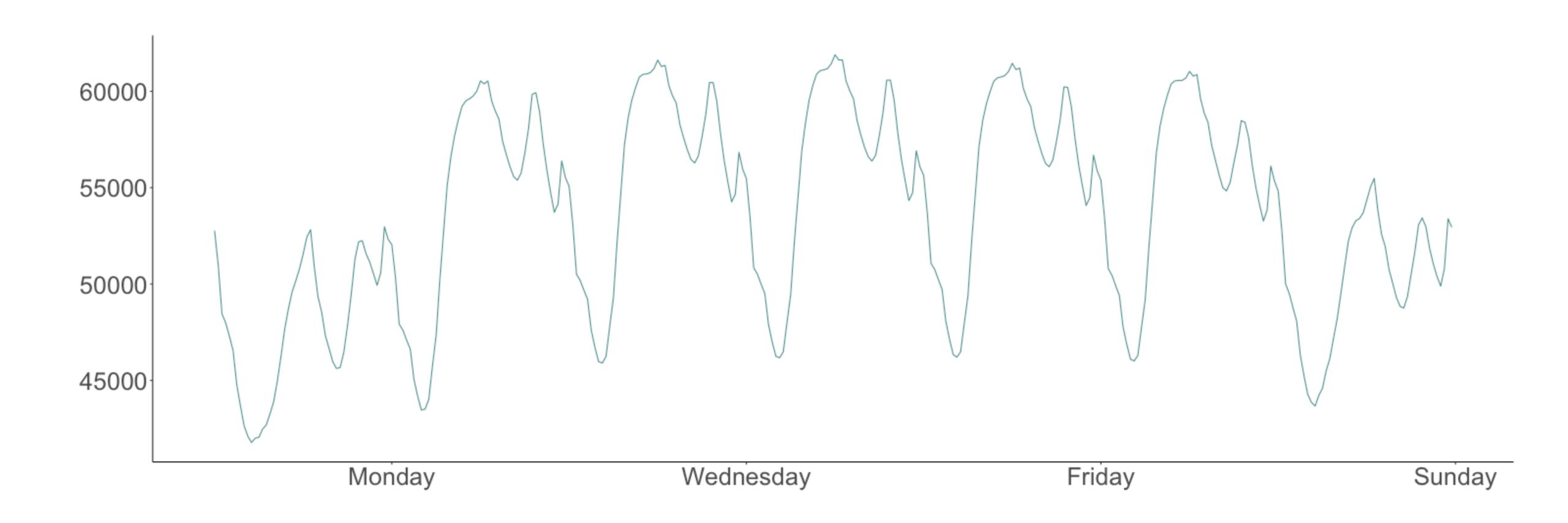


French electricity consumption (MW) in half-hourly time steps from January 1, 2012 to June 22, 2023

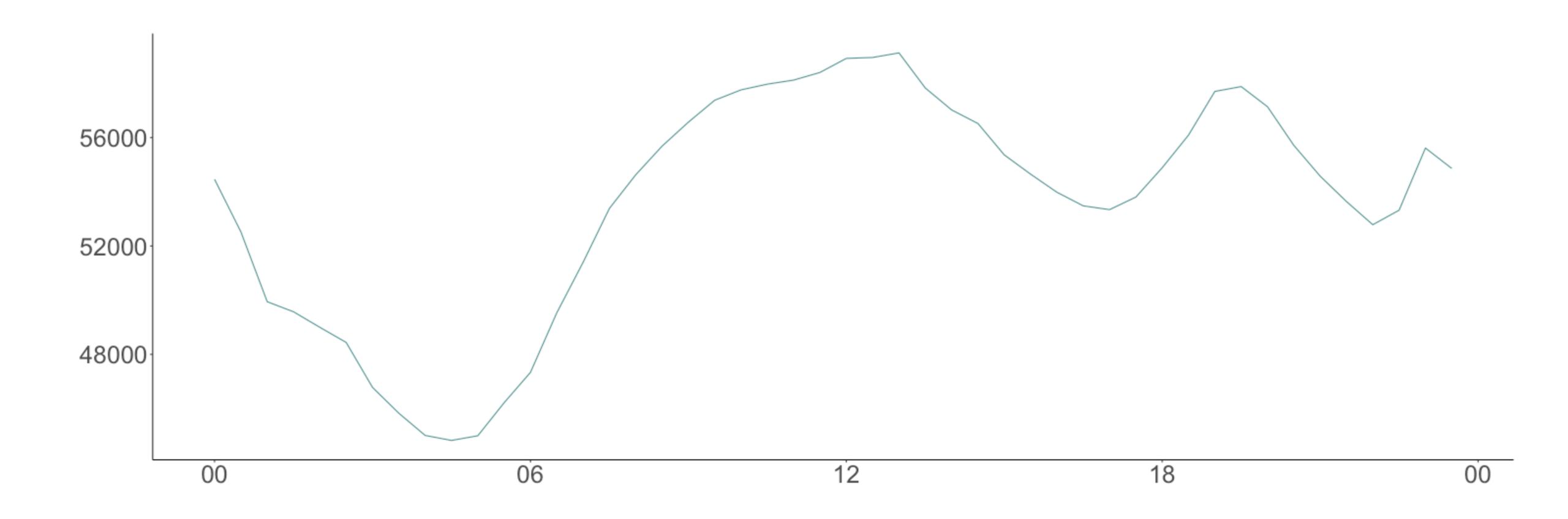
Descriptive analysis - average annual load



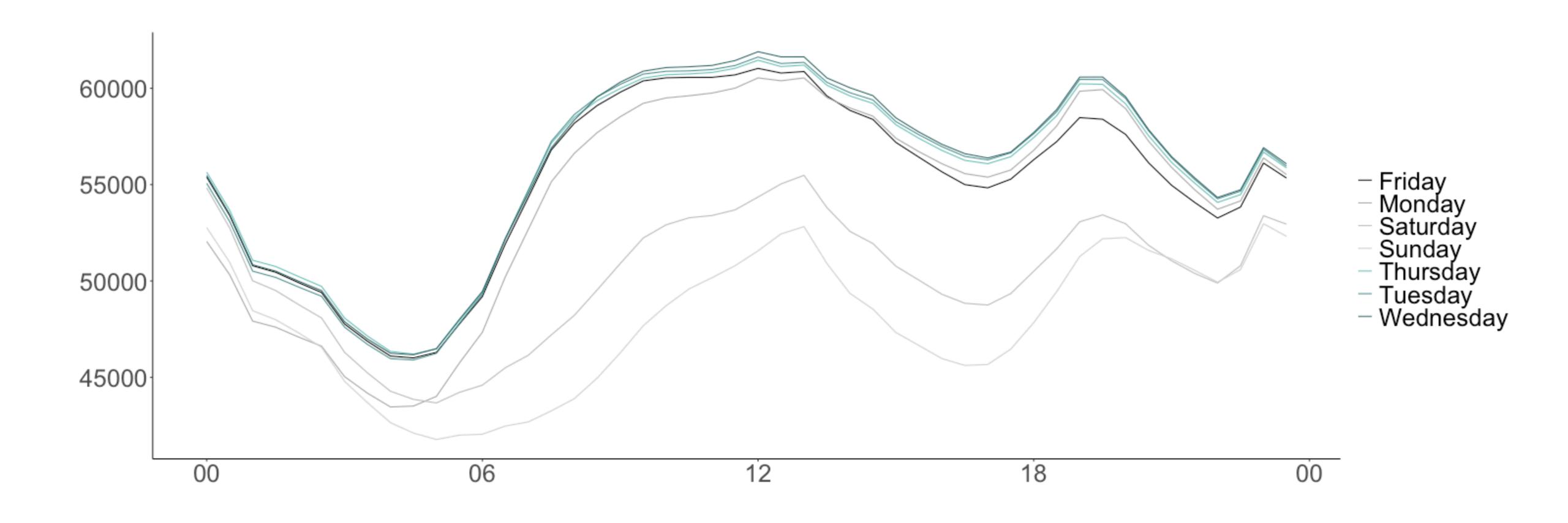
Descriptive analysis - average weekly load



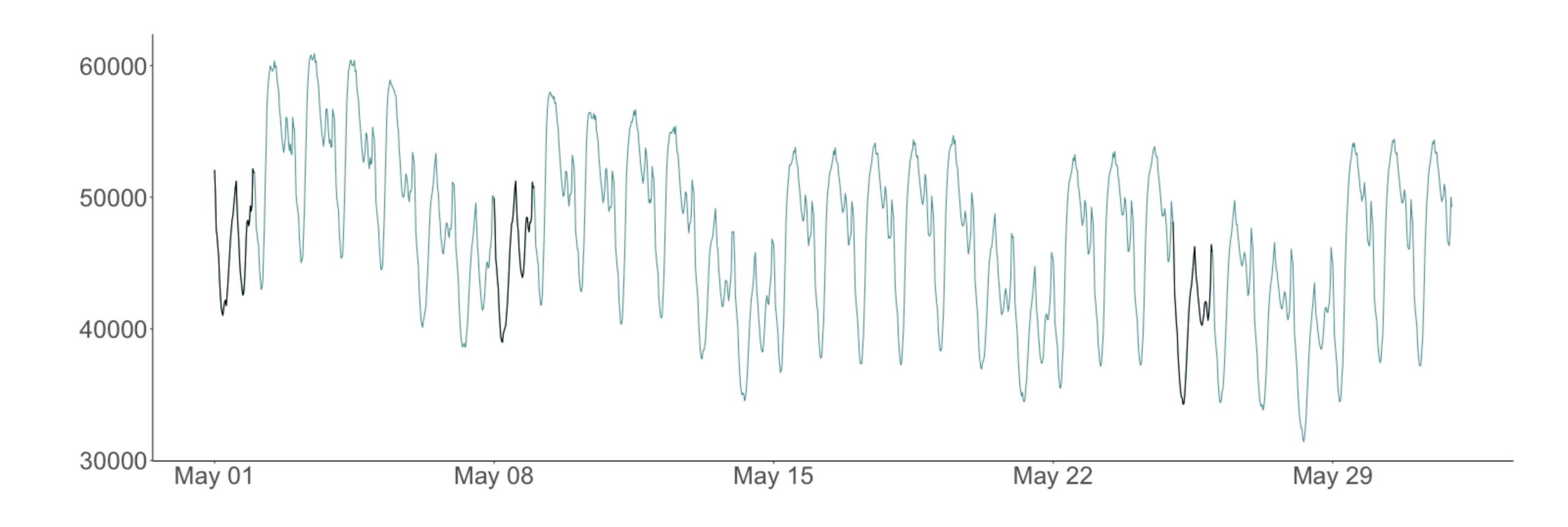
Descriptive analysis - average daily load



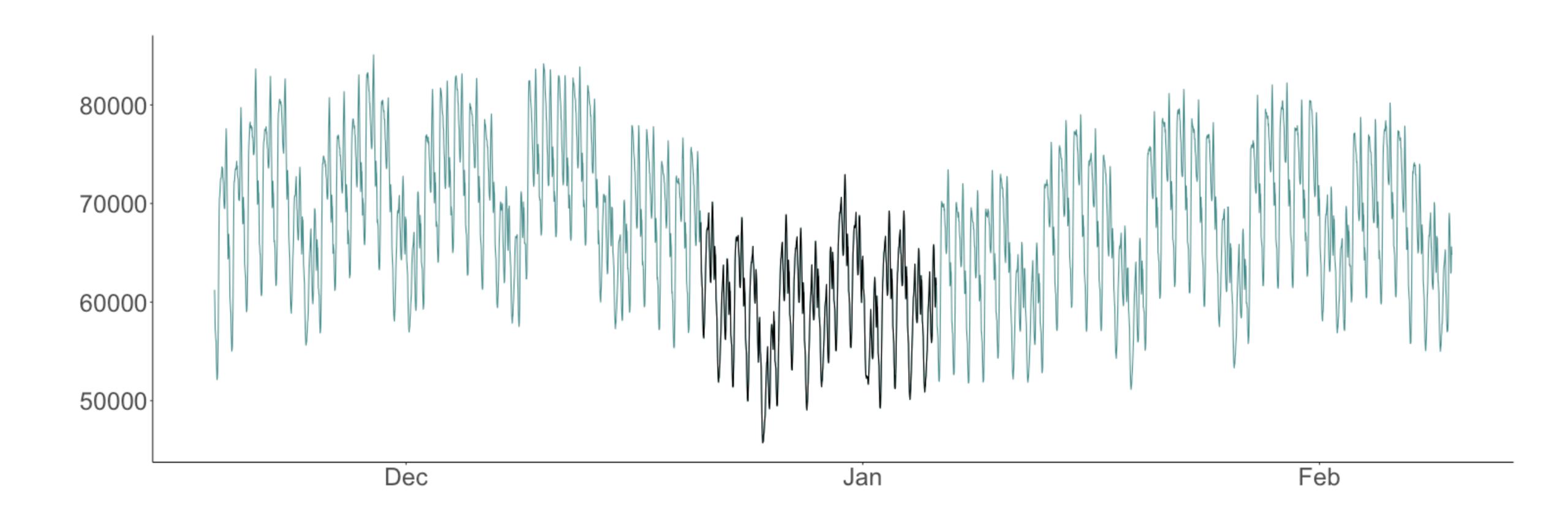
Descriptive analysis - type of day



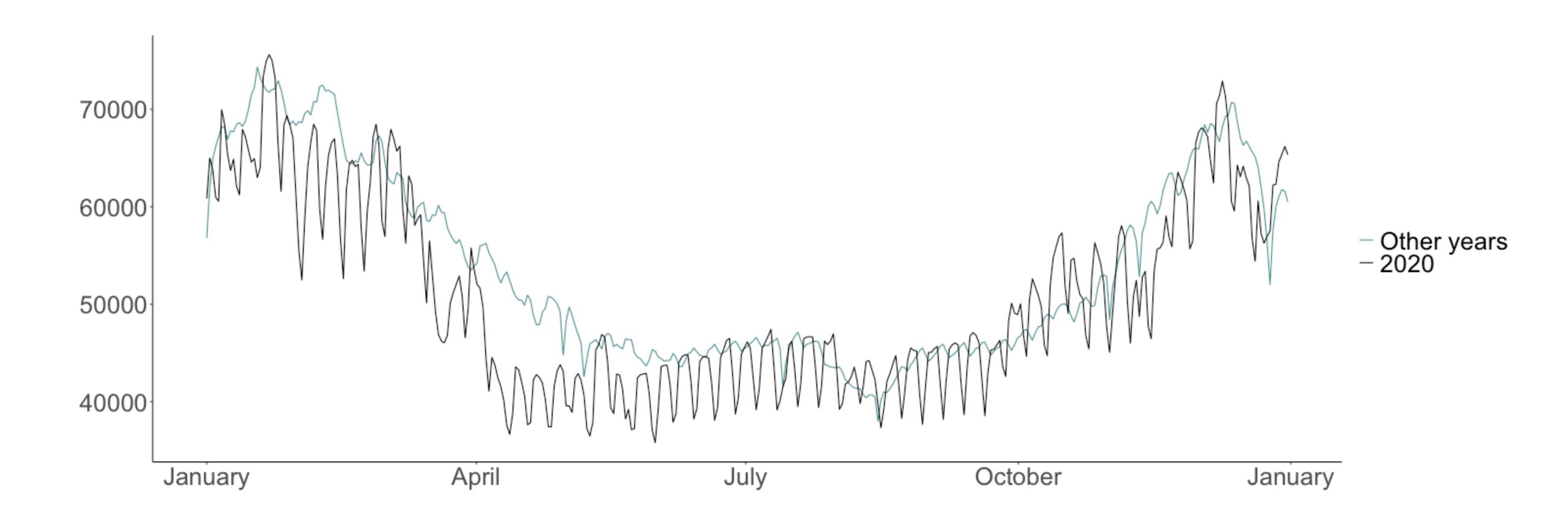
Descriptive analysis - day off



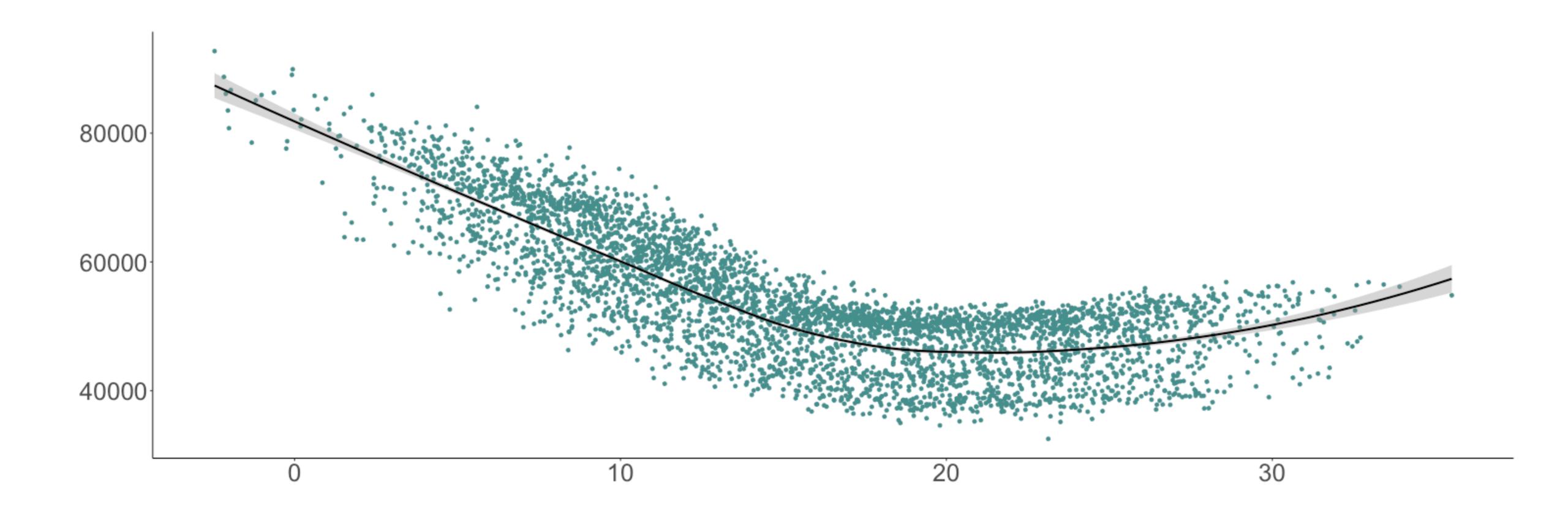
Descriptive analysis - holidays



Descriptive analysis - rare event



Descriptive analysis - temperature impact at 4p.m.



Additional data and assumption

https://donneespubliques.meteofrance.fr/

39 weather stations in mainland France (excluding Corsica)

Observations at three-hour time step of:

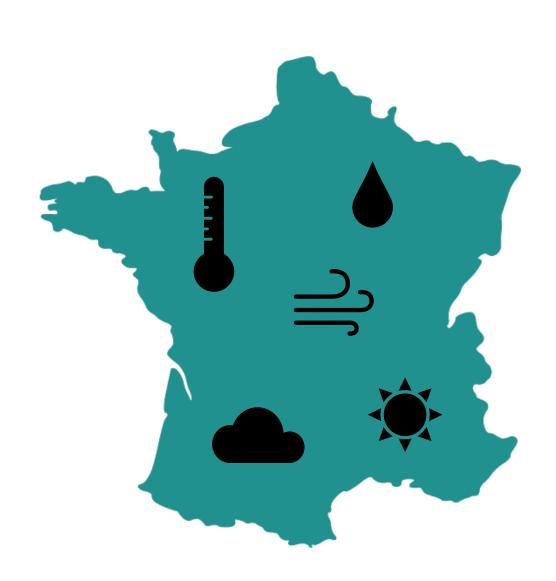
Temperature,

Nebulosity,

Wind Speed,

Humidity,

Precipitation etc.







Météo France has forecast the weather perfectly, so we will use the observations as if they were forecasts

That's all folks!

TP \rightarrow https://drive.google.com/drive/folders/10H6oH0dolXN9QxOSKuEfLbF44HkN5QfB? usp=share_link