



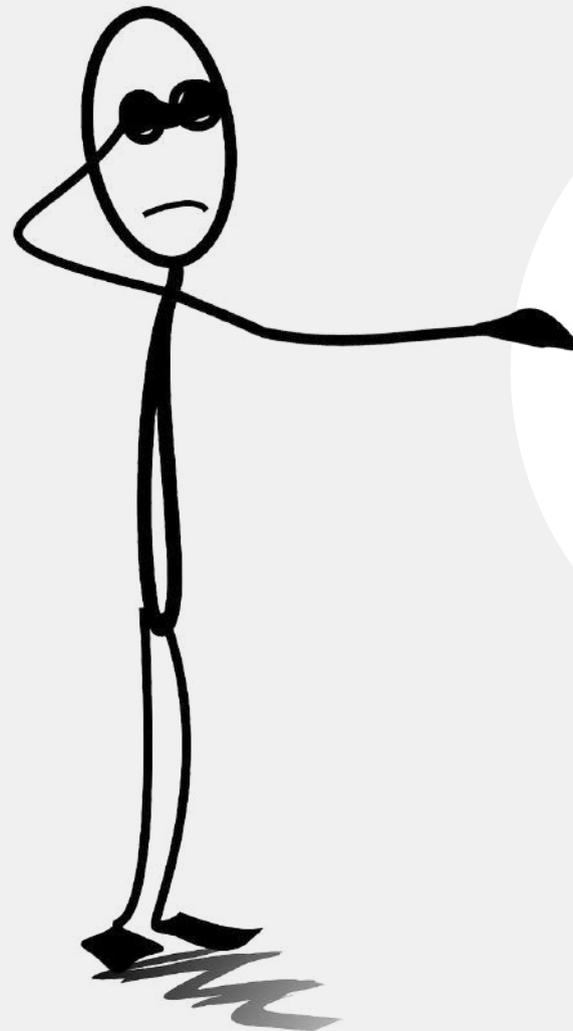
A meta-learning approach for short-term energy load, generation, and price forecasting

11th International Ruhr Energy Conference (INREC)

Master Thesis, University of Applied Sciences Hamm-Lippstadt

Sten Kramin

HOW FORECASTING METHODS ARE SELECTED TODAY...



Linear Regression

LSTM

ARIMA

Reccurent Neural Network

Deep AR

Moving Average

Exponential Smoothing

N-BEATS

SARIMAX

Prophet

Temporal Fusion Transformer

Temporal Fusion Transformer

Prophet

Multiple Linear Regression

Multiple Linear Regression

CNN

Prophet

Reccurent Neural Network

HOW THEY COULD BE SELECTED...



Analysis of the input time series



Trained model selects most suitable forecasting model



Performing the forecast

01 Forecast of Time Series



02 Model Selection



03 Case Study



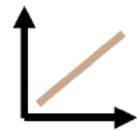
04 Conclusion & Outlook



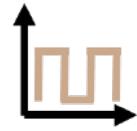
AGENDA

A meta-learning approach
for short-term energy load,
generation, and price forecasting

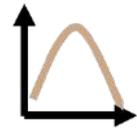
TIME SERIES COMPONENTS



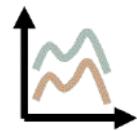
Trend



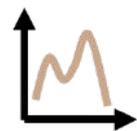
Seasonality



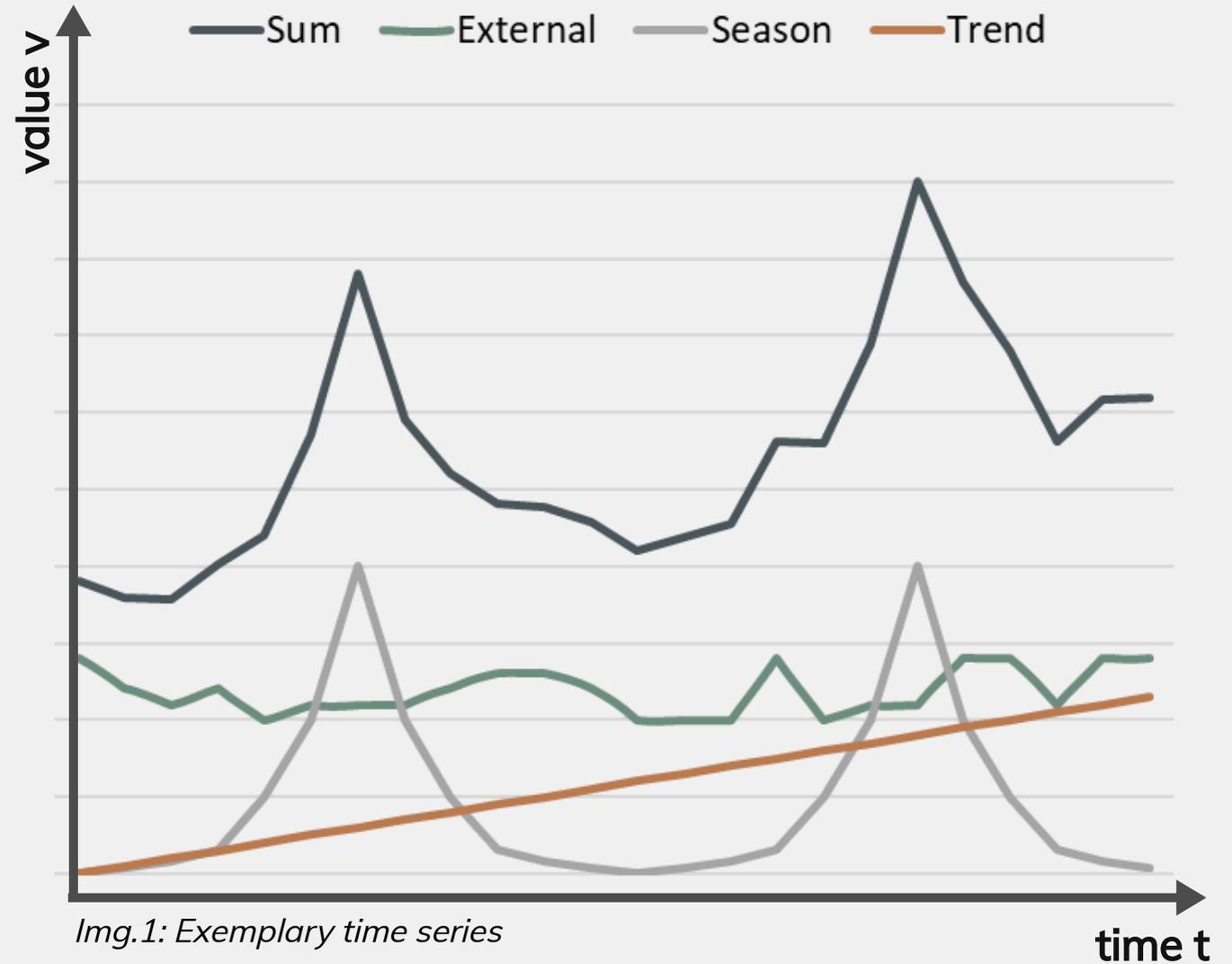
Saturating Growth



Exogenous Dependencies



White Noise



SHORT-TERM FORECASTING METHODS

Well-performing benchmark methods (Ensafi 2022, Nguyen 2021)

Complexity



Simple Statistical Methods

- Multiple Linear Regression

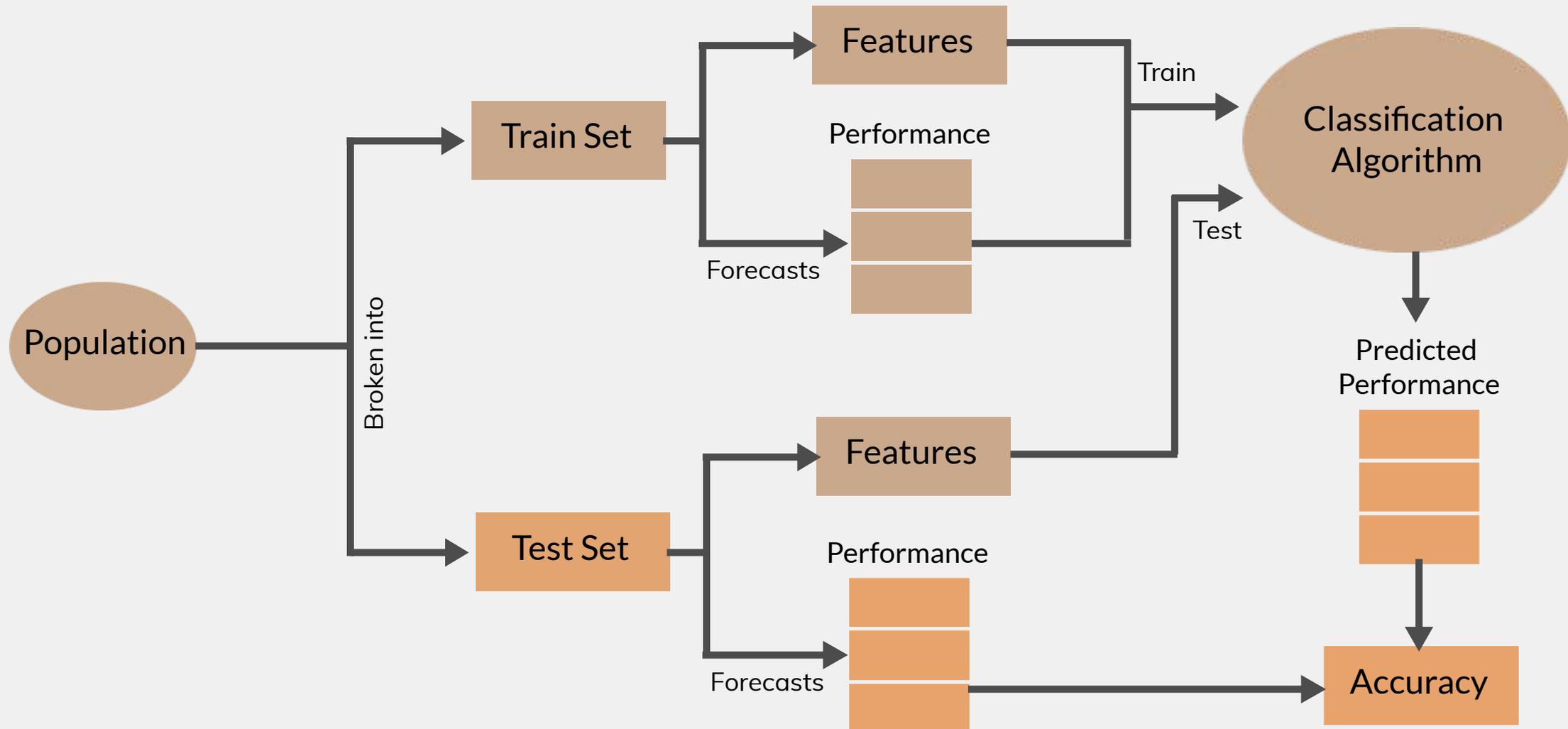
Complex Statistical Methods

- Prophet
- SARIMAX (Seasonal Auto-Regressive Integrated Moving Average X)

Advanced Methods

- Feedforward Neural Network
- Recurrent Neural Network (including Memory)
- Long Short-Term Memory (including Forget Function)

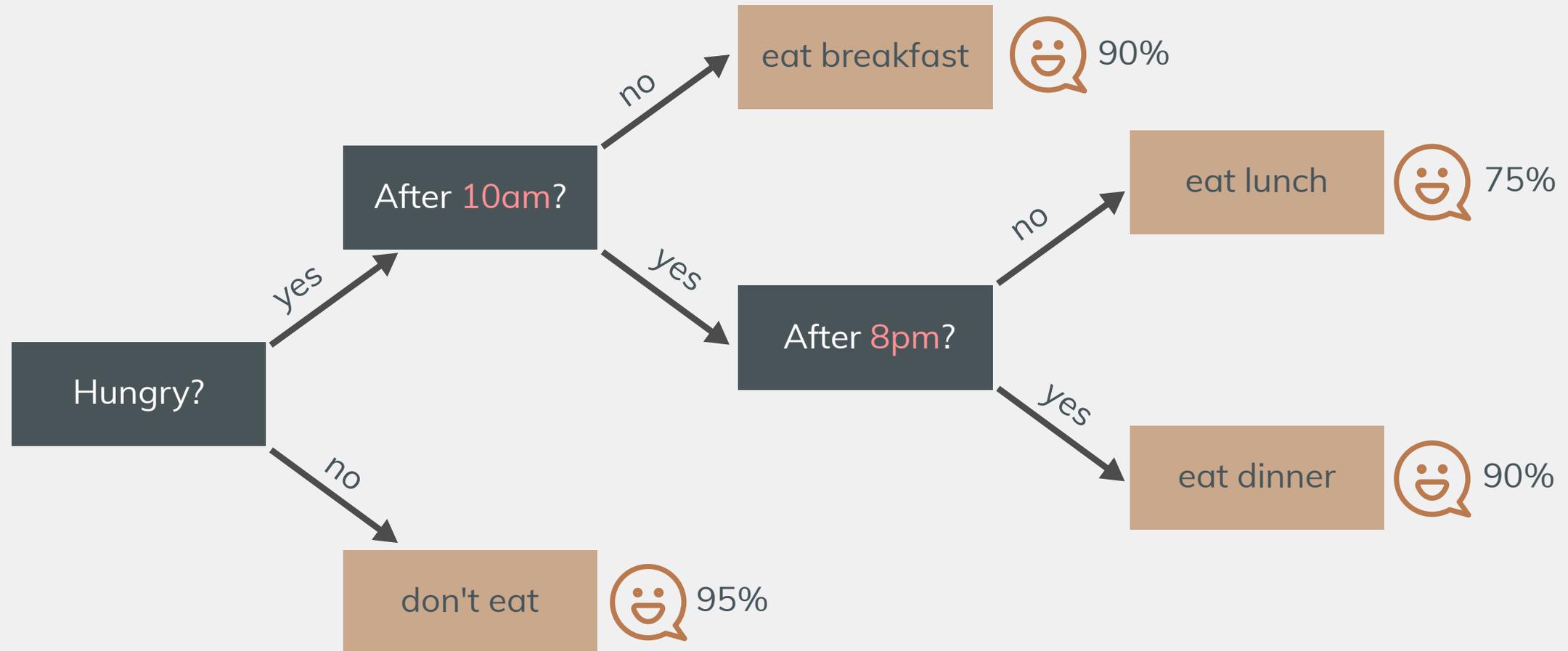
MODEL SELECTION



Img.2: Generalized procedure of a time series forecasting model selection
(Based on: Talagala 2018, Smith-Miles 2009)

RANDOM FOREST CLASSIFIER

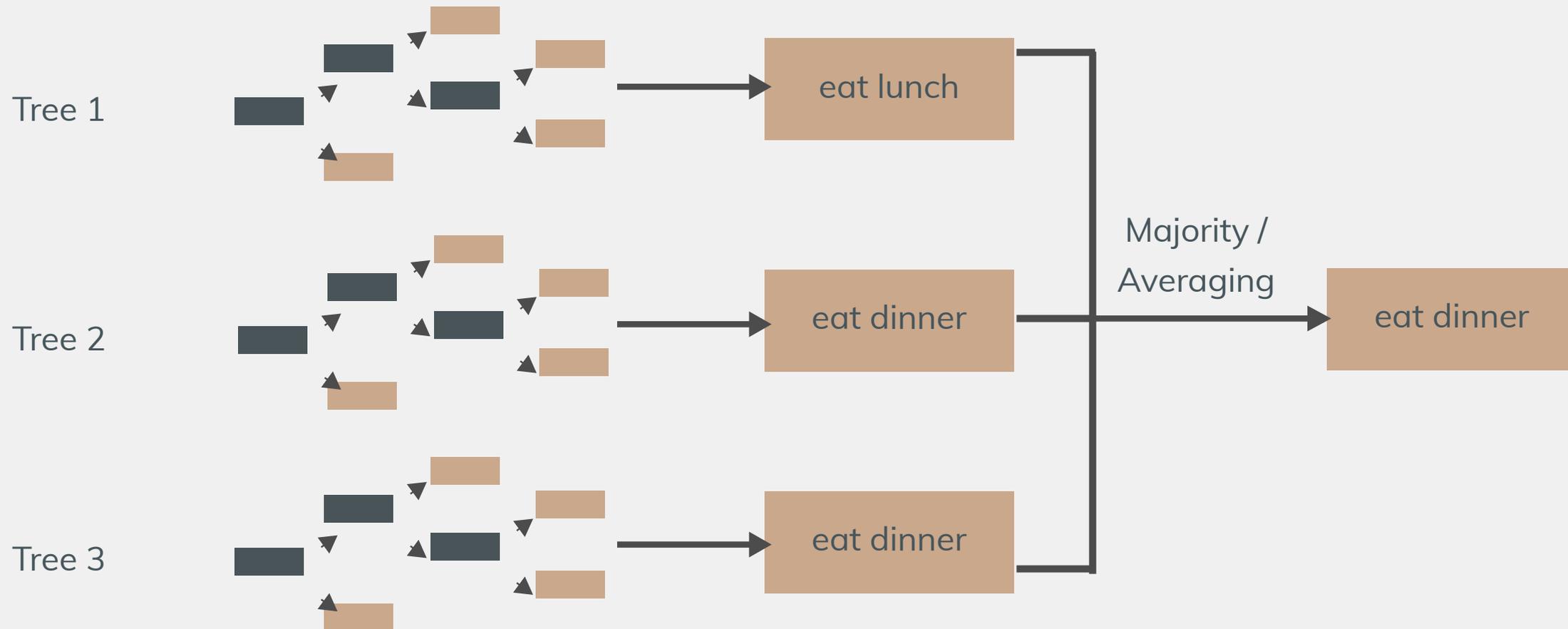
Applied classification algorithm



Img.3: Exemplary decision tree (Meltzer, 2021)

RANDOM FOREST CLASSIFIER II

Applied classification algorithm



Img.4: Generalized process of a random forest classifier (Meltzer, 2021)

CASE STUDY

A meta-learning approach
for short-term energy load,
generation, and price forecasting

INPUT DATA

37 bidding zones of 28 European countries

Energy Time Series (ENTSO-E, 2022)

- Day-Ahead Price
- Generation (Solar and Wind)
- Load

Weather Time Series (Copernicus, 2022)

- Wind speed
- Solar irradiance
- Air temperature

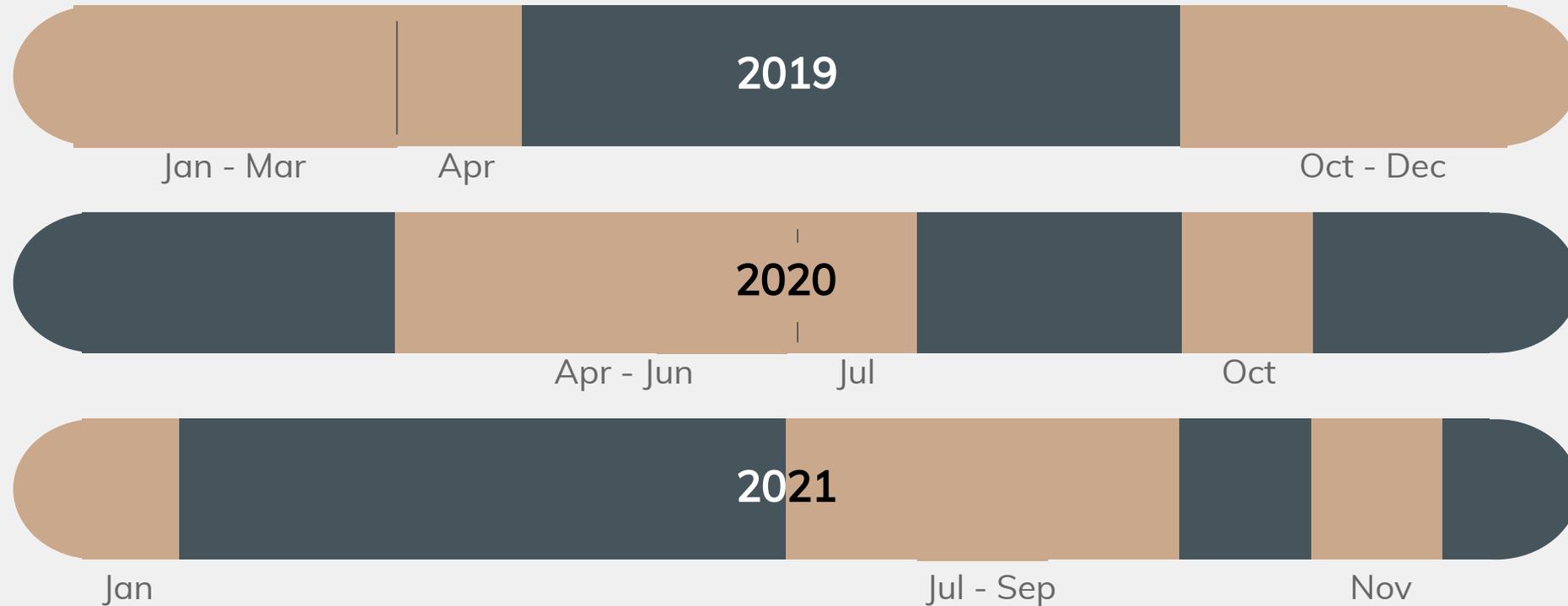
-  Country with one bidding zone
-  Country with multiple bidding zones
-  Data unavailable



Img.5: Overview over available data per country

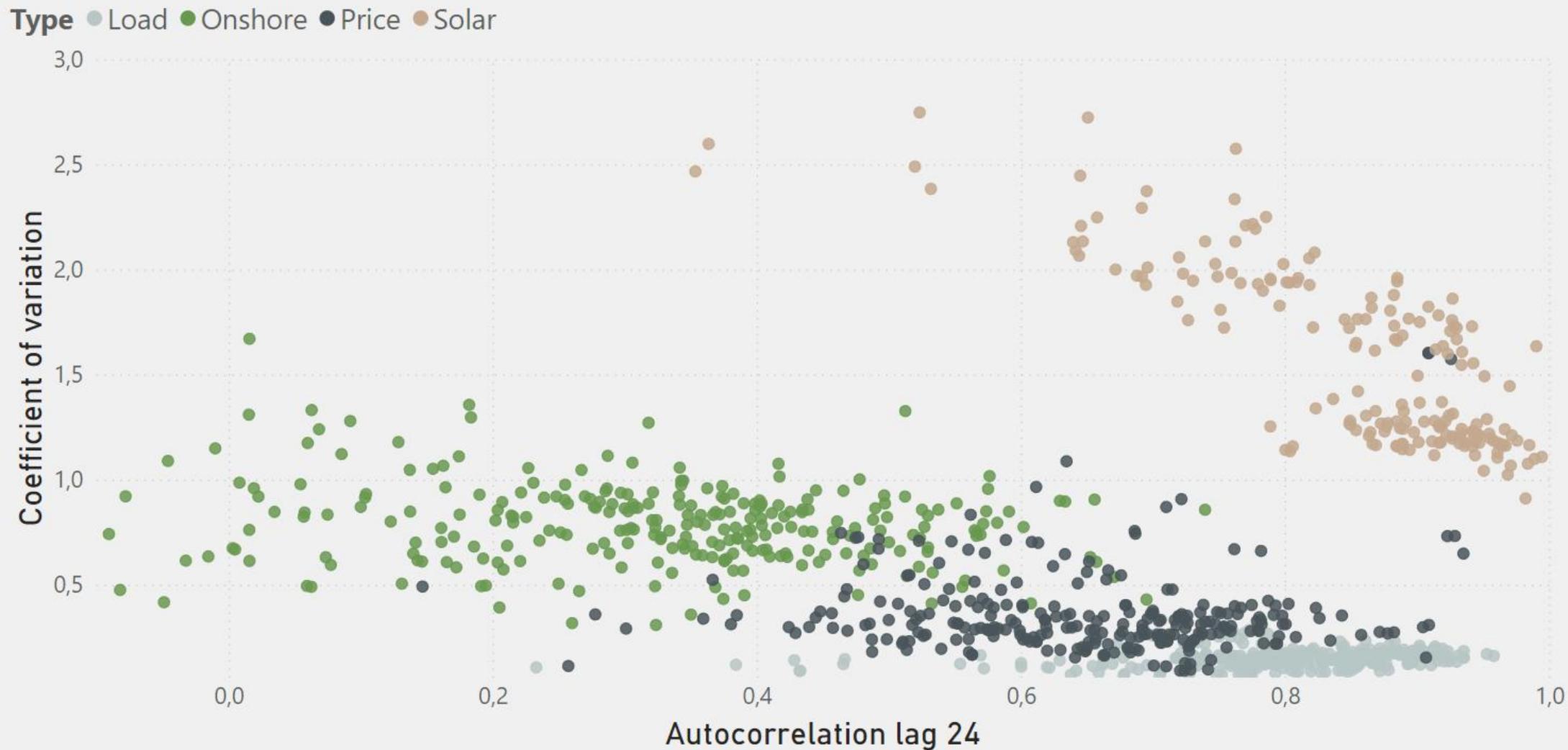
INPUT DATA II

Img.6: Selected time frames



9 Time Frames x 37 Bidding Zones x 4 Energy Series Types - Missing Series
= 1026 Sample Time Series

INPUT DATA III



Img.7: Comparison of the sample time series

METHODOLOGY - FEATURES

According to the methodology on slide 9.

8 Time series features were used for the model selection:

- **Count of timestamps**
- **Coefficient of variation** of the endogenous variables
- **Coefficient of variation** of the hour and day-type averages
- **Autocorrelation** of the endogenous variables for the lags 1 and 24.
- **Pearson Correlation** between the endogenous and it's exogenous variables
(First and second highest)

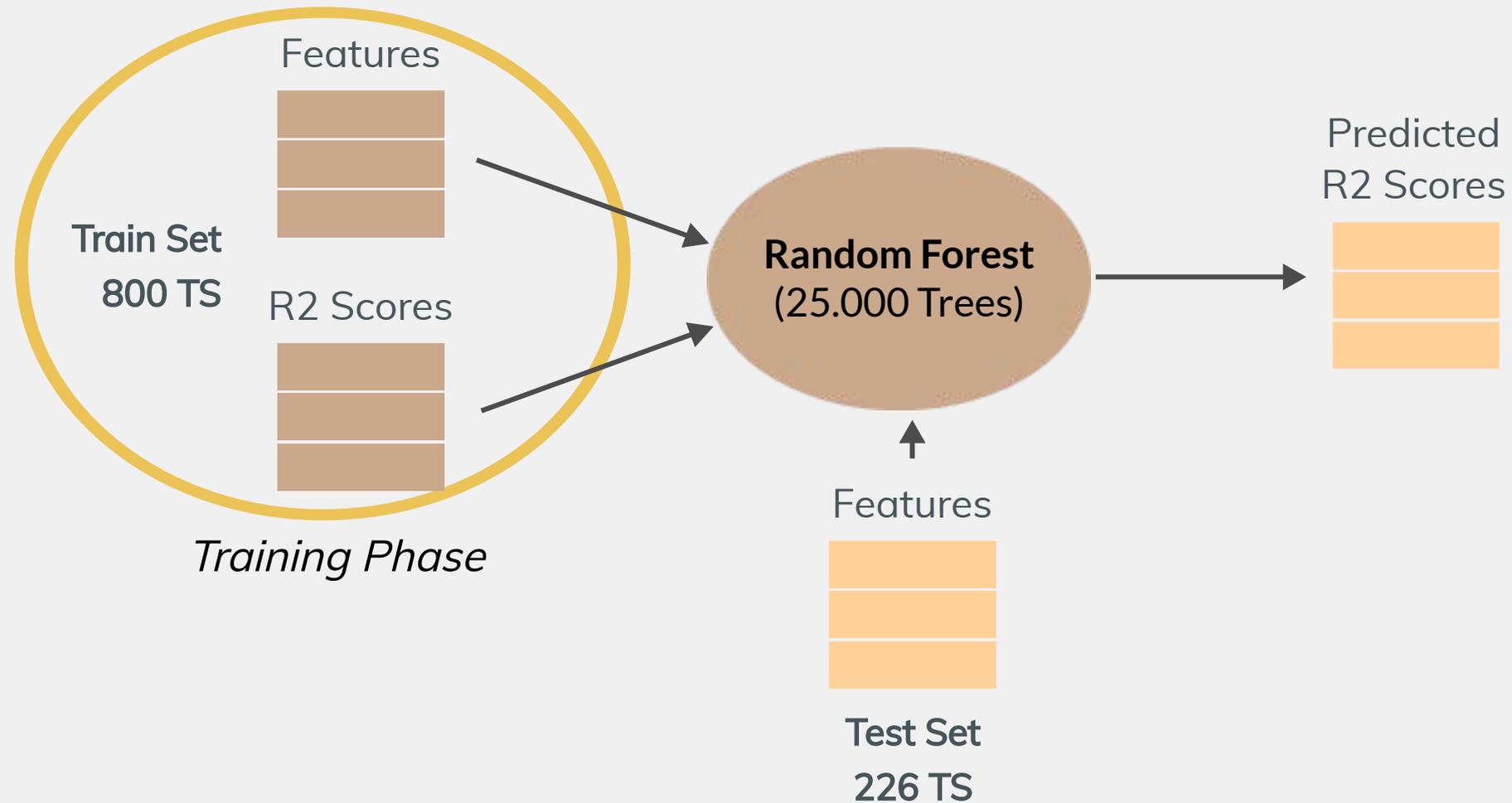
METHODOLOGY - FORECASTING METHODS

According to the methodology on slide 9.

10 Methods for day-ahead forecasts were used:

- 3 variants of **Multiple Linear Regression** (different availability of information)
- 3 variants of **SARIMAX** (different model parameters)
- 2 variants of **Prophet** (different availability of information)
- 2 variants of **LSTM** (high amount of cells vs. high amount of iterations)

METHODOLOGY - RANDOM FOREST

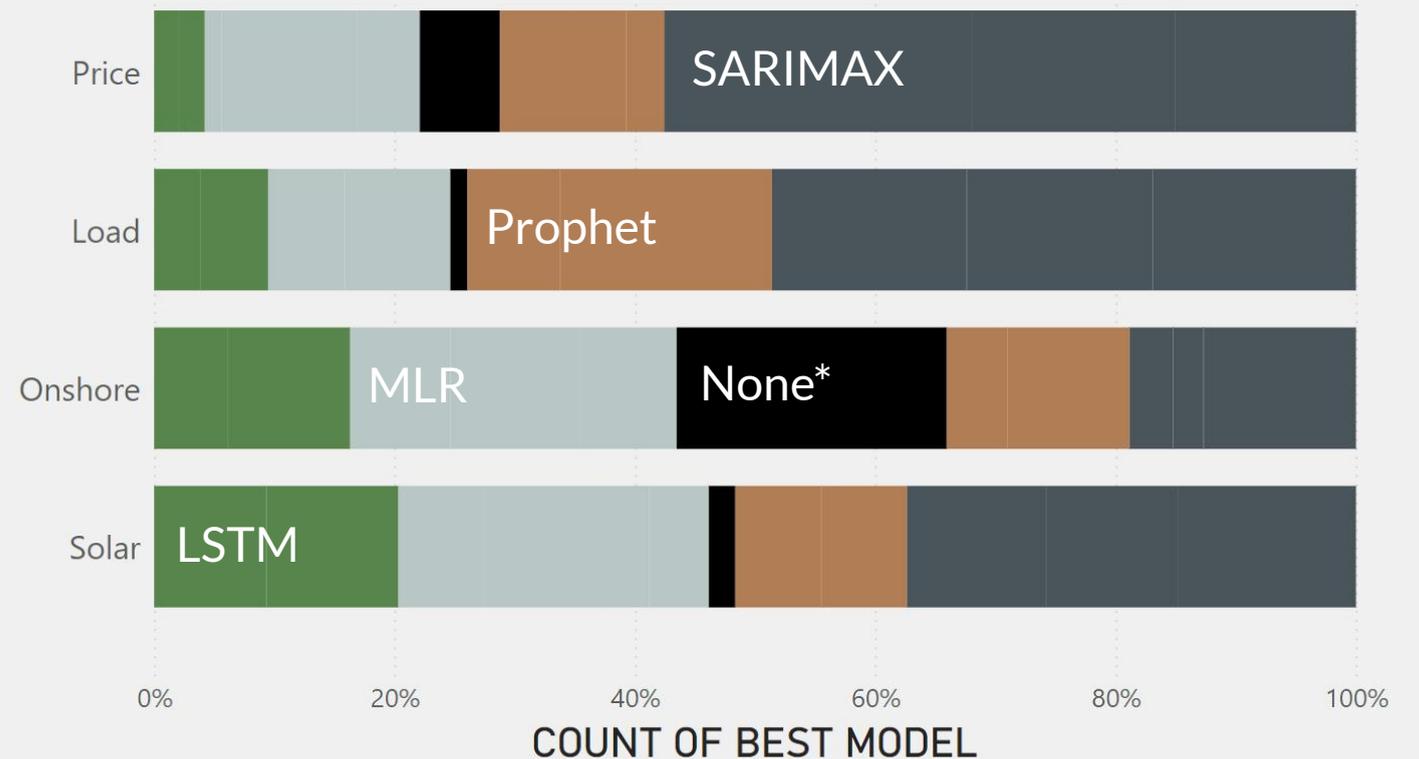


Img.8: Representation of the applied train and test procedure

RESULTS - FORECASTING PERFORMANCE

Median R2 Scores:

1. SARIMAX (0,1,2 1,0,1 24)	0.583
2. Prophet ExoTime	0.577
3. SARIMAX (1,1,1 1,0,1 24)	0.572
[...]	
8. MLR ExoTime	0.467
9. SARIMAX (2,0,1 2,0,0 24)	0.374
10. MLR Exo	0.089



Img.9: Distribution of the best forecasting methods per time series type

*Cases where no forecasting method had sufficient accuracy (R2 Score <= 0)..

RESULTS - MODEL SELECTION

Result performance indicators as relative share of the test population.



Suggested model and best model match



Model with close-to-best accuracy suggested ($\Delta R^2 < 0.05$)



Model with far-from-best accuracy suggested ($\Delta R^2 > 0.2$)

- the choice of the right forecasting method has a high impact on the quality of the forecast.
- time series consist of many components that are essential when choosing a forecasting model.
- with the help of the feature-based forecast model selection framework, the ideal model for energy time series can be predicted with a promising accuracy.
- thinking in terms of higher scales, a universally applicable and highly accurate model selection framework could be created.



**CONCLUSION
& OUTLOOK**

REFERENCES

- Copernicus.** "Climate and energy indicators for Europe from 1979 to present derived from reanalysis." (2022). <https://cds.climate.copernicus.eu/cdsapp#!/dataset/sis-energy-derived-reanalysis?tab=overview>.
- Ensafi et al.** "Time-series forecasting of seasonal items sales using machine learning - A comparative analysis." (2022). *International Journal of Information Management Data*.
- ENTSO-E.** "Central collection and publication of electricity generation, transportation and consumption data and information for the pan-European market" (2022). <https://transparency.entsoe.eu/>.
- Meltzer.** "What Is Random Forest?" (2021). <https://careerfoundry.com/en/blog/data-analytics/what-is-random-forest/>
- Nguyen.** "End-to-End Time Series Analysis and Forecasting: a Trio of SARIMAX, LSTM and Prophet." (2021). <https://towardsdatascience.com/end-to-end-time-series-analysis-and-forecasting-a-trio-of-sarimax-lstm-and-prophet-part-1-306367e57db8>.
- Smith-Miles.** "Cross-disciplinary perspectives on meta-learning for algorithm selection." (2009). *ACM Computing Surveys (CSUR)*.
- Talalga et al.** "Meta-learning how to forecast time." (2018). <https://www.monash.edu/business/ebs/our-research/publications/ebs/wp06-2018.pdf>